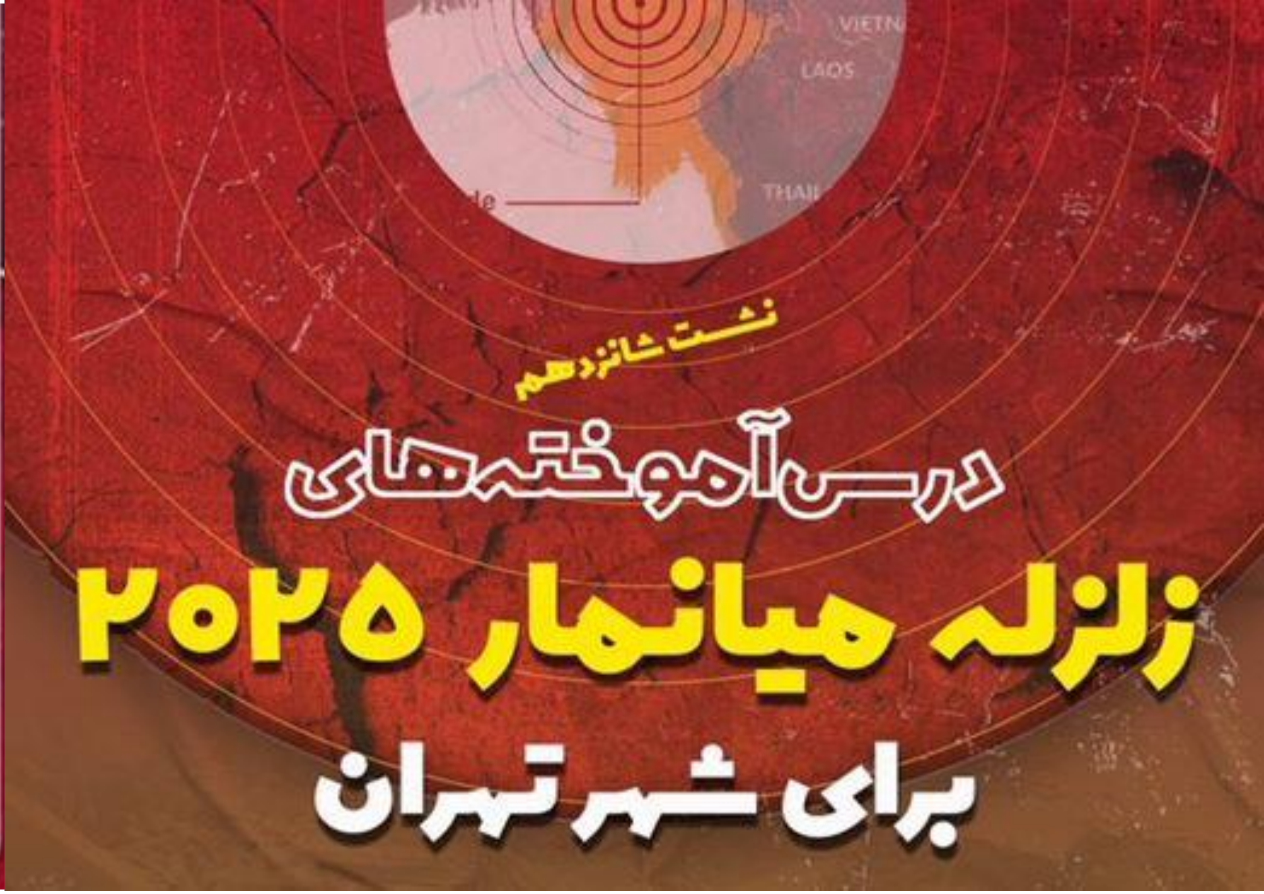


پایش ماهواره ای و ارزیابی سرسع خسارتها

بابک منصوری
پژوهشگاه بین المللی زلزله شناسی و مهندسی زلزله

وبینار یکشنبه ۲۱ اردیبهشت ماه ۱۴۰۴

زلزله‌های ویرانگر نظیر زلزله اخیر میانمار، به‌دلیل گستردگی خسارات و محدودیت منابع پاسخ‌دهی، نیازمند ارزیابی سریع و نسبتا دقیق از گستره و میزان آسیب هستند.

روش‌های سنتی، مانند بازدید میدانی، بسیار زمان‌بر و پرهزینه‌اند.

روش‌های نوین مبتنی بر پردازش تصاویر ماهواره ای و توفیقات یادگیری عمیق Deep Learning ابزارهایی توانمند برای تحلیل سریع در گستره‌ی مناطق آسیب‌دیده فراهم آورده‌اند.

GEO-CAN damage assignment protocol

Post- Disaster Building Damage Assessment Using Satellite And Aerial Imagery Interpretation, Field Verification
And Modeling Techniques

~ 2010 vision - Crowd Sourcing Visual Inspection/Observation by Volunteers

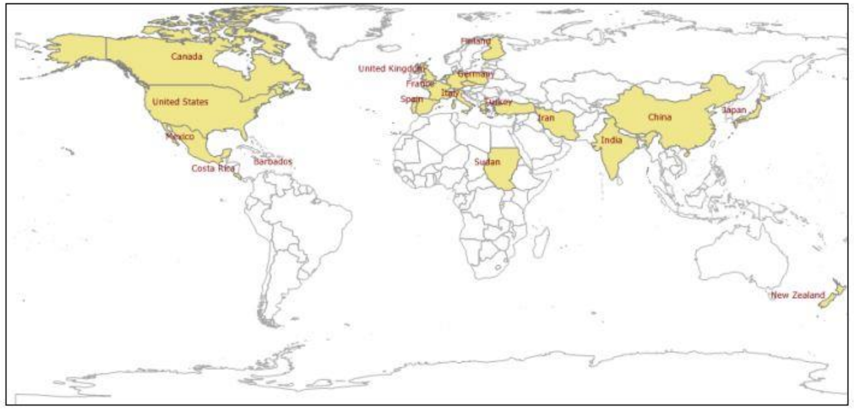
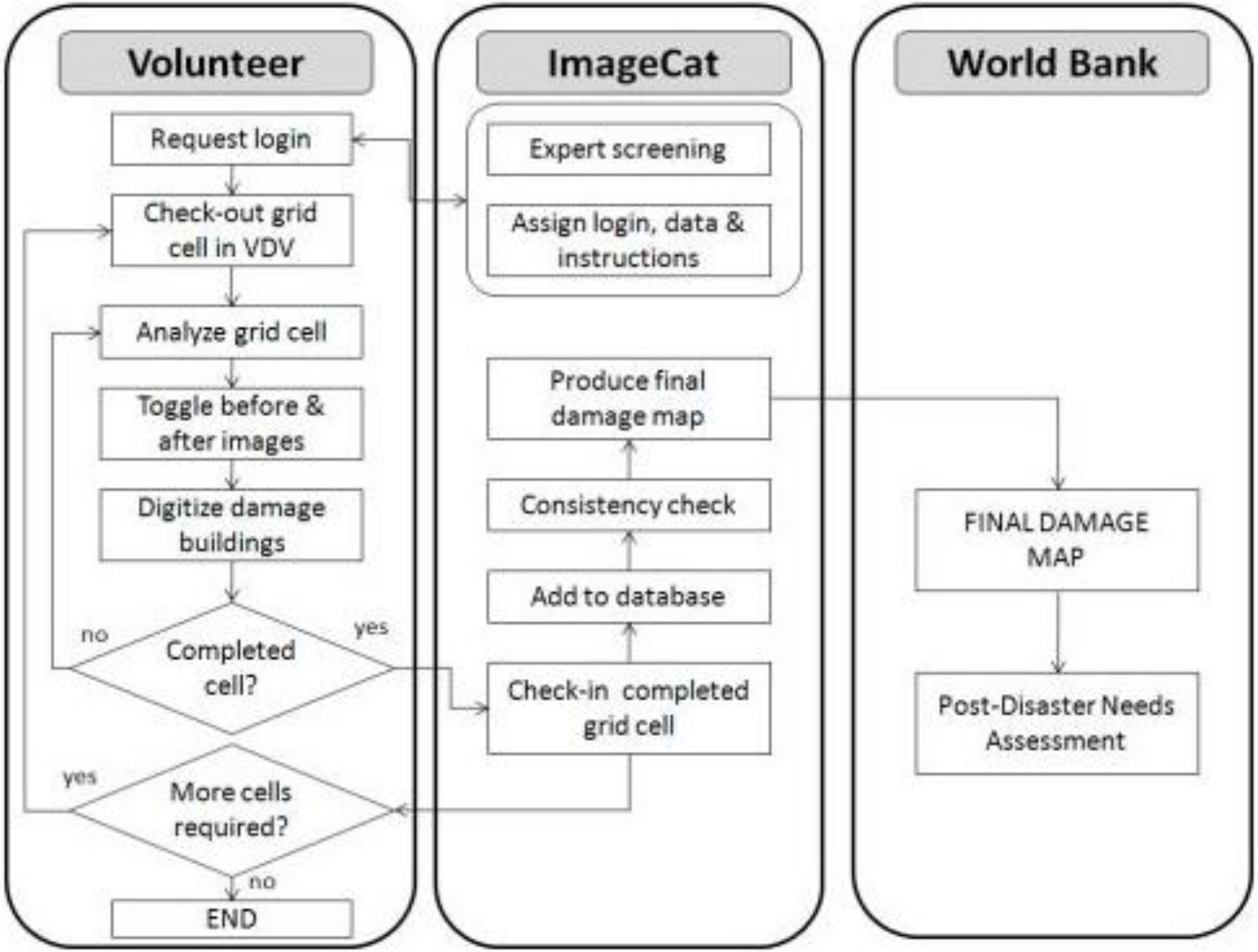


Figure 5.2 Nations with Participating GEO-CAN Members (in yellow)

GEO-CAN damage assessment protocol emphasized the importance of accurate damage assignments



https://www.gfdrr.org/sites/default/files/publication/2010haitiearthquakepost-disasterbuildingdamageassessment.pdf

UN-SPIDER's Role in Facilitating Access to Satellite Imagery

- Gateway to space-based information for disaster management support,

- connecting disaster management community with space community.

- Facilitating access to satellite imagery from various providers.
- UN-SPIDER has agreements with space-related stakeholders to showcase or provide high-resolution imagery to member states affected by disasters.

Provide Satellite Imagery from Space Startups and Academia

UN-SPIDER: Timely access to critical data during disasters - acquiring necessary imagery, through International Disaster Charter, Sentinel Asia, or Copernicus EMS.

Progress:

GeoCan (Crowd Sourcing Visual Inspection)
UNITAR (UN-organizations by Visual Satellite Imagery Interpretation)
UNSPIDER Facilitation(towards efficient AI Deep Learning Methods)

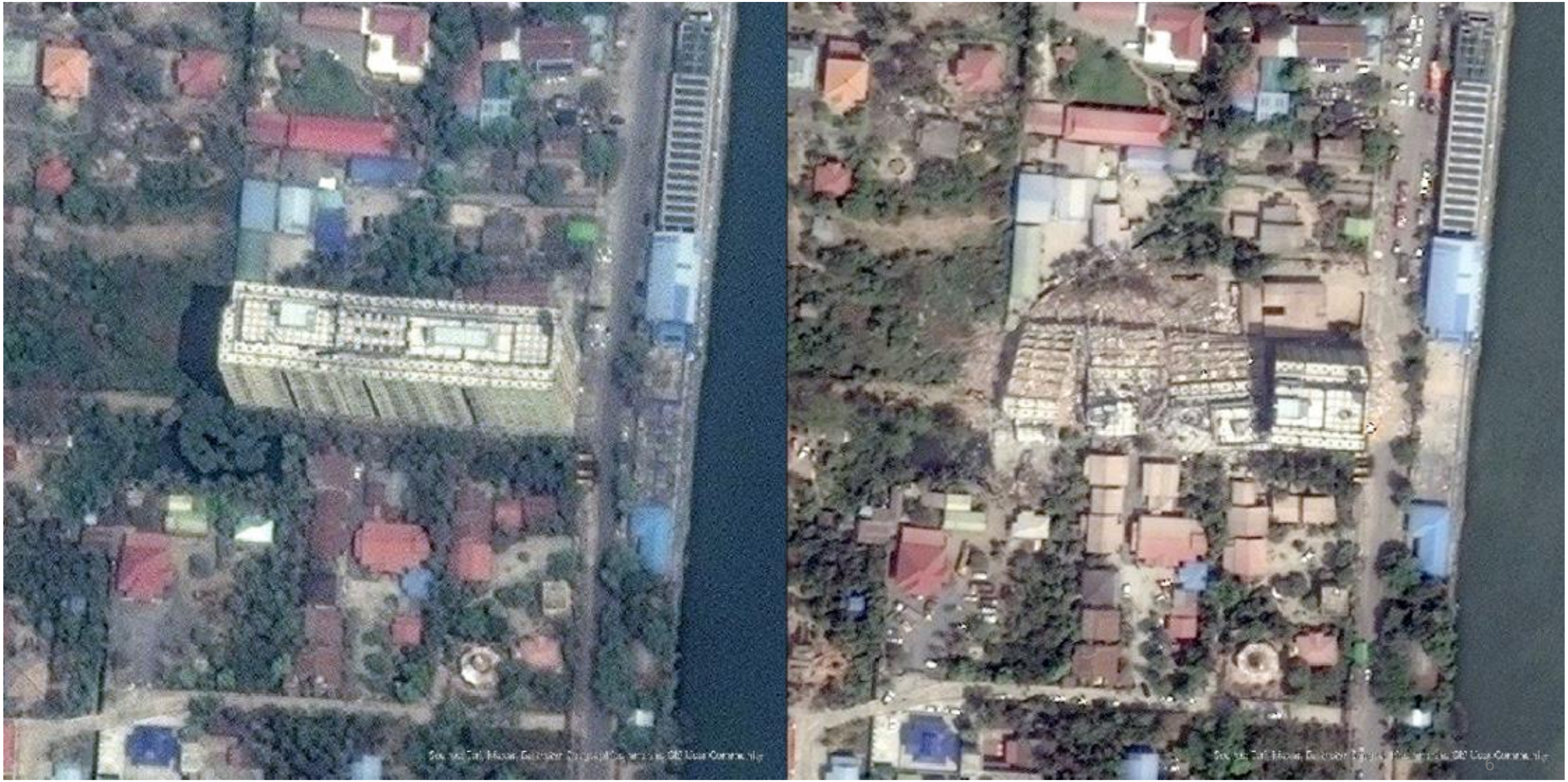
Key Stakeholders - satellite imagery during this disaster:
•Axelspace
•Maxar Technologies
•Open Cosmos
•Synspective Inc.
•China National Space Administration
•National Disaster Reduction Center of China, Ministry of Emergency Management
•Collaborative Network of Disaster Data Response (CDDR)
•Aerospace Information Research Institute of the Chinese Academy of Sciences (AIR)

Table for Shared Satellite Imagery

Satellite	Provider	Sensor
AIRSAT-01	CASC	SAR
HT2-03C	PIESAT	SAR
AS-01	Sixiang Tech.	SAR
HY1D	CNSA	Optical
ZY1E,1F	CRESDA	Optical
HY1C	CNSA	Optical
GF3C	CNSA	SAR
GF1,4,6	CNSA	Optical
BJ-3	CHINASIWEI	Optical
JL-1	CGSTL	Optical
StriX-1,2,3	Synspective Inc.	SAR
GRUS-1	Axelspace	Optical
WorldView-1,2	Maxar Technologies	Optical
WorldViewLegion-2,3,4	Maxar Technologies	Optical
HAMMER	Open Cosmos	Hyperspectral
MANTIS	Open Cosmos	Optical

Collapse of Sky Villa Condominium building by Optical imagery

Maxar Technologies provided very high-resolution optical satellite imagery, WorldView Legion (Resolution: 30cm),



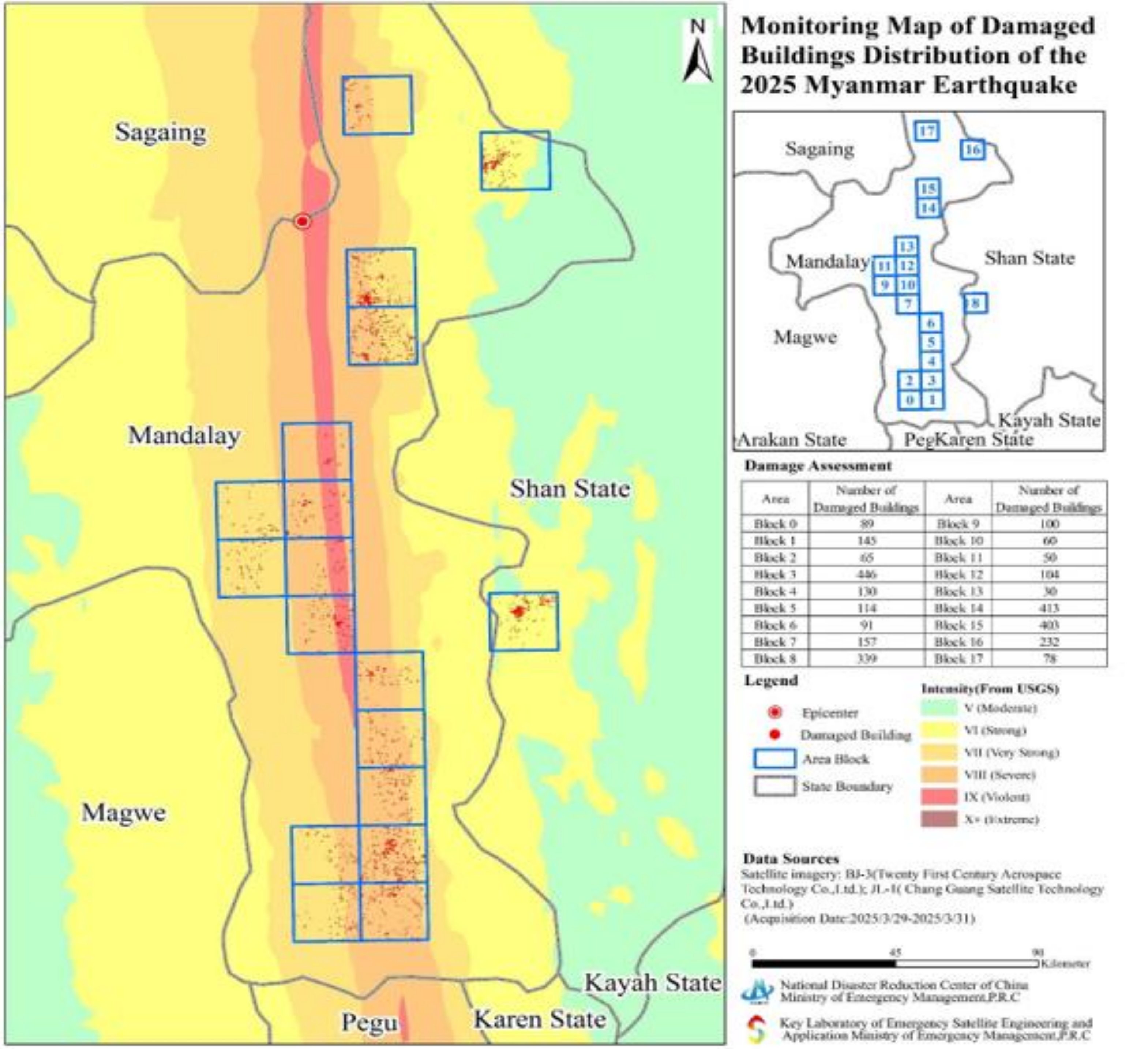
Rapid Damage Assessment using satellite imagery and Deep Learning

National Disaster Reduction Center of China (NDRCC)
Laboratory of Emergency Satellite Engineering (China)
Application of the Ministry of Emergency Management (China),
Collaboration with UN-SPIDER,

High-resolution Damaged Buildings Map in central Myanmar for 2025 Myanmar

Satellite Imagery: BJ-3 (Beijing-3) and JL-1 (Jilin-1) satellite constellations between 29 and 31 March 2025

Change Detection models: Deep Learning methodology identifies building damages in high-intensity zones.



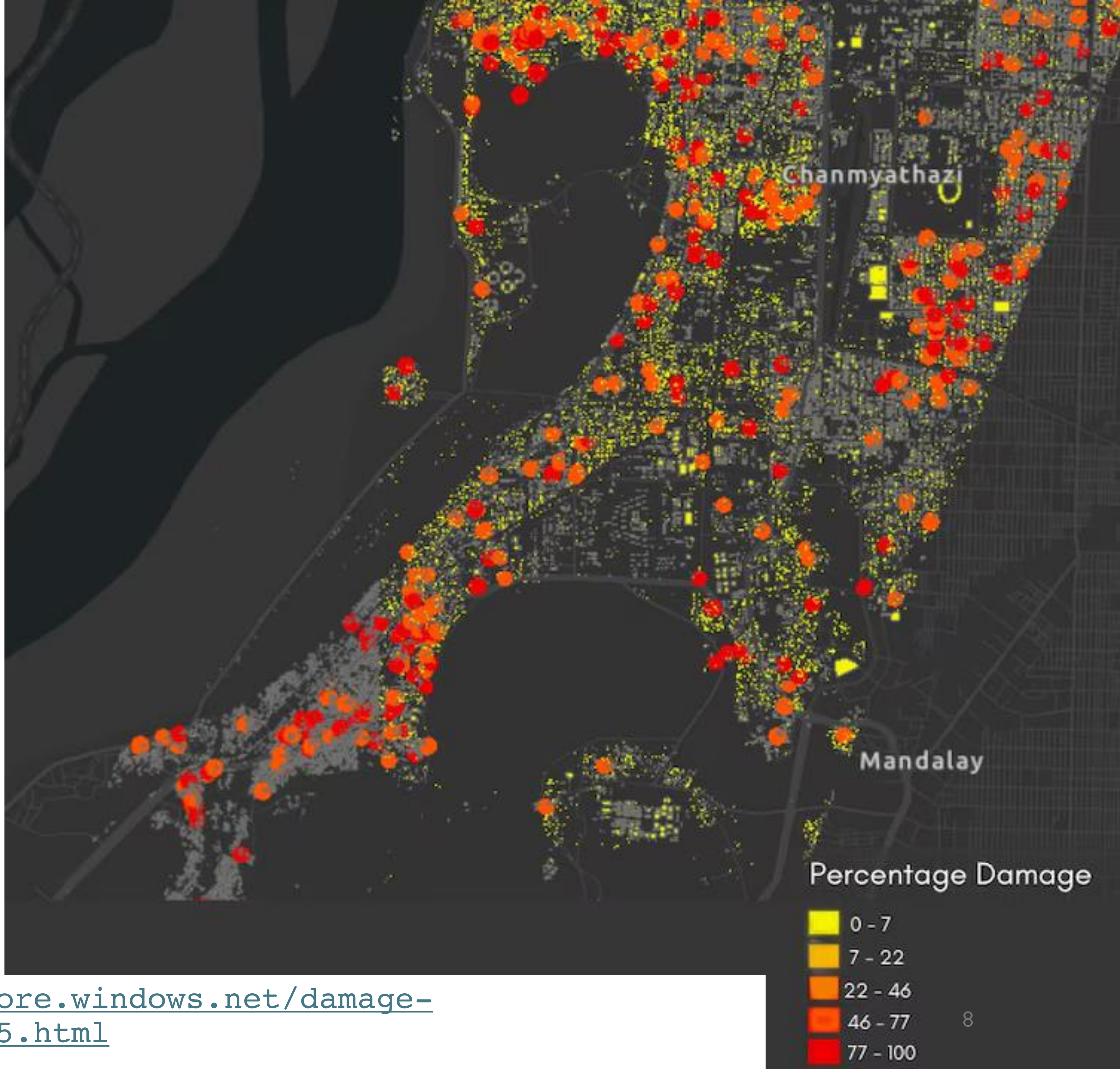
Area	Number of Damaged Buildings	Area	Number of Damaged Buildings
Block 0	89	Block 9	100
Block 1	145	Block 10	60
Block 2	65	Block 11	50
Block 3	446	Block 12	104
Block 4	130	Block 13	30
Block 5	114	Block 14	413
Block 6	91	Block 15	403
Block 7	157	Block 16	232
Block 8	339	Block 17	78

Myanmar earthquake: How AI is helping in quick damage assessment

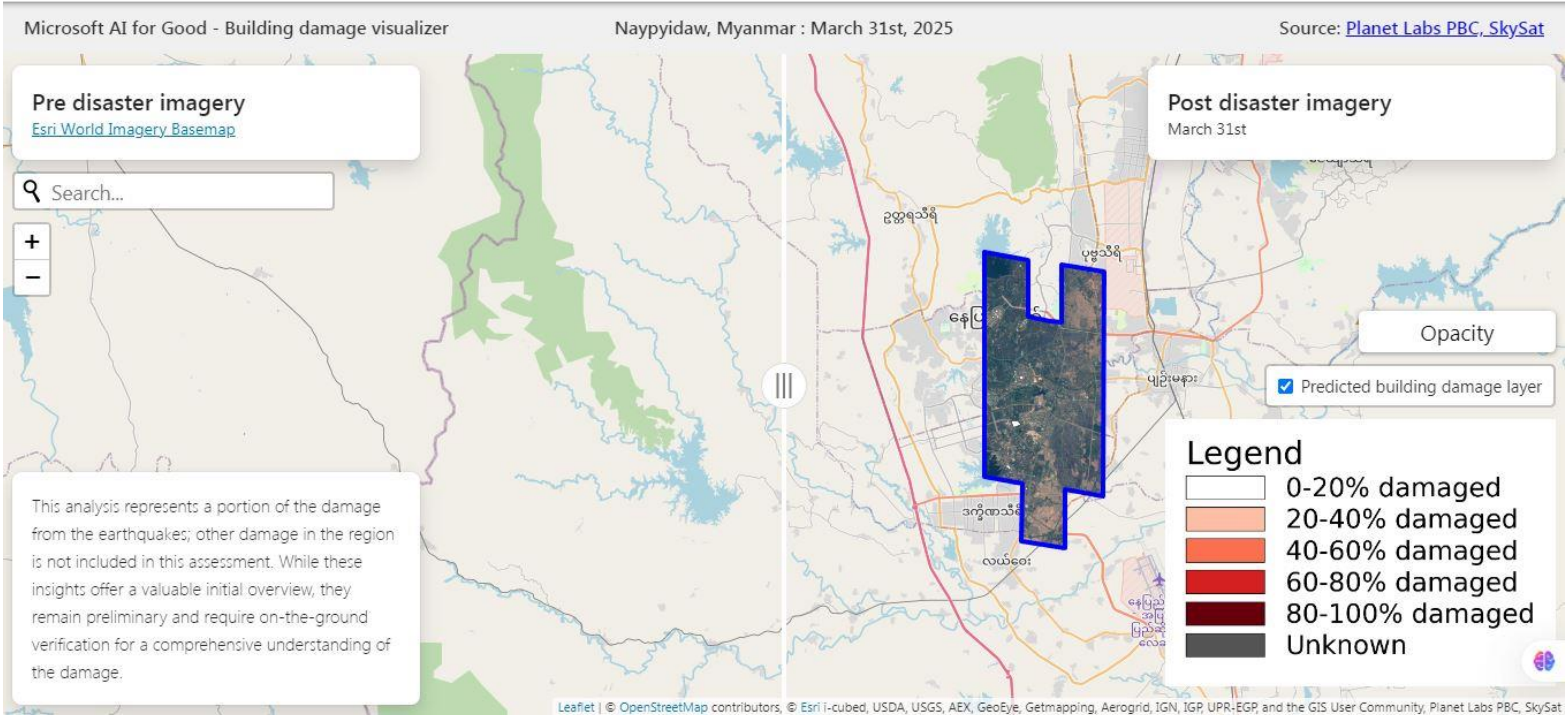
Over 2,000 damaged structures identified in quake-hit Mandalay city

Using Microsoft's AI-powered damage assessment tool.

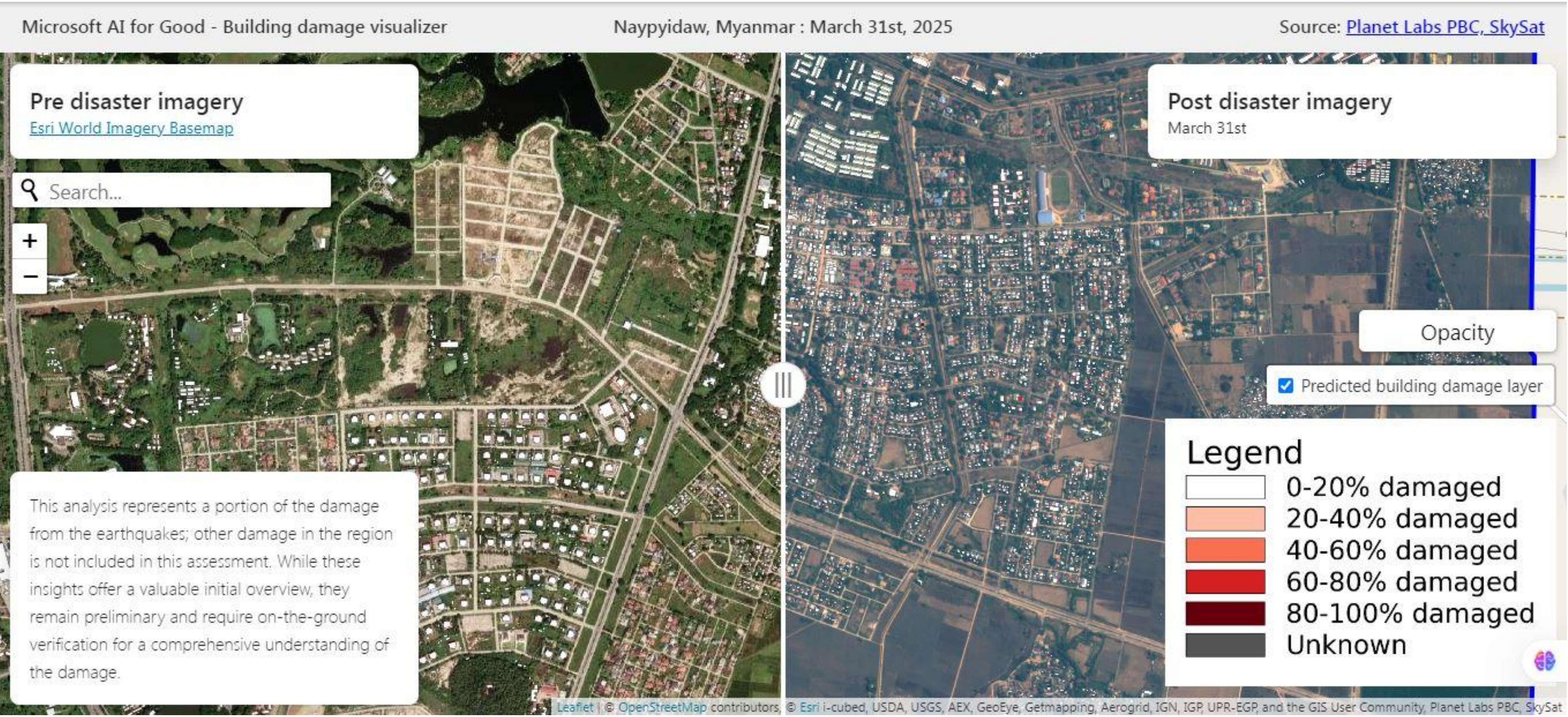
Based on remote-sensing data from Planet Labs PBC, Microsoft’s AI for Good lab processed and visualised damage across more than 1.81 lakh buildings in Mandalay, Myanmar.



https://satelliteimagerydemostg.z5.web.core.windows.net/damage-assessment/naypyidaw_earthquake_3_31_2025.html



https://satelliteimagerydemostg.z5.web.core.windows.net/damage-assessment/naypyidaw_earthquake_3_31_2025.html



Microsoft AI for Good - Building damage visualizer
Naypyidaw, Myanmar : March 31st, 2025
Source: Planet Labs PBC, SkySat
Pre disaster imagery
Esri World Imagery Basemap
Search...
Post disaster imagery
March 31st
Opacity
Predicted building damage layer
Legend
0-20% damaged
20-40% damaged
40-60% damaged
60-80% damaged
80-100% damaged
Unknown
This analysis represents a portion of the damage from the earthquakes; other damage in the region is not included in this assessment. While these insights offer a valuable initial overview, they remain preliminary and require on-the-ground verification for a comprehensive understanding of the damage.
Leaflet | © OpenStreetMap contributors, © Esri i-cubed, USDA, USGS, AEX, GeoEye, Getmapping, Aerogrid, IGN, IGP, UPR-EGP, and the GIS User Community, Planet Labs PBC, SkySat

انتقال یادگیری: (Transfer Learning)
چالش اصلی در آموزش مدل‌های یادگیری عمیق در استخراج نقشه خرابی: **کمبود داده‌های برچسب‌خورده** (labelled data) برای زلزله جدید

مفهوم:
استفاده از دانش مدل‌های آموزش‌دیده روی مجموعه‌داده‌های بزرگ و مشابه برای حل مسائل جدید با داده‌های محدود است.
به جای آموزش یک مدل از صفر (که زمان‌بر و داده‌بر است)، یک مدل پیش‌آموزش‌دیده (Pre-trained) بر روی داده‌های خاص مسأله جدید تنظیم یا (Fine- Tune)می گردد.

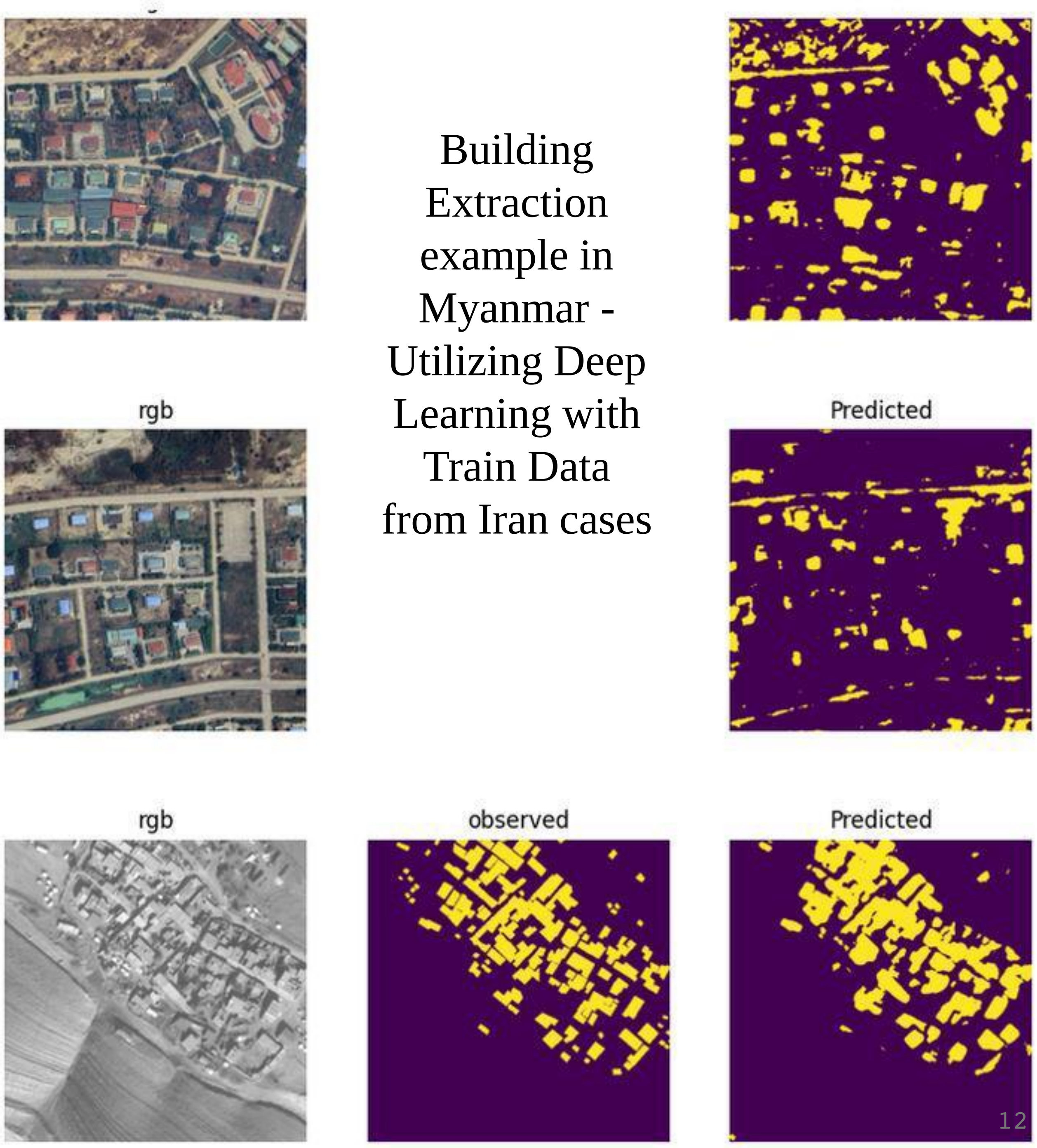
کاربرد در پروژه زلزله میانمار : یا استفاده از تجربیات جهانی در زلزله جدید:
مدل‌های **پیش‌آموزش‌دیده روی مجموعه‌داده‌های عمومی** مانند ImageNet یا داده‌های سنجش از دور مشابه، انتخاب می گردد.
این مدل‌ها در درک ویژگی‌های تصویری مانند لبه‌ها، بافت‌ها و الگوهای خرابی، **دانش اولیه** را دارند.
مدل با تعداد کمی تصویر برچسب‌خورده از زلزله مورد نظر **تنظیم مجدد** می گردد تا با ویژگی‌های خاص منطقه تطبیق یابد.

مزایای انتقال یادگیری:
کاهش نیاز به داده‌های زیاد: کافی است تعداد کمی تصویر برچسب‌خورده تهیه شود.
صرفه‌جویی در زمان و منابع محاسباتی: آموزش مدل جدید از صفر زمان‌بر است، ولی تنظیمات سریع‌تر انجام می‌شود.
افزایش دقت: مدل می‌تواند ویژگی‌های پیچیده خرابی را بهتر یاد بگیرد.

انتقال یادگیری: (Transfer Learning)

کاربرد در پروژه زلزله میانمار یا موارد جدید دیگر:

- مدل‌های **پیش‌آموزش‌دیده روی مجموعه‌داده‌های عمومی** مانند ImageNet یا داده‌های سنجش از دور مشابه، انتخاب می گردد.
- این مدل‌ها در درک ویژگی‌های تصویری مانند لبه‌ها، بافت‌ها و الگوهای خرابی، **دانش اولیه** را دارند.
- مدل با تعداد کمی تصویر برچسب‌خورده از زلزله مورد نظر **تنظیم مجدد** می گردد تا با ویژگی‌های خاص منطقه تطبیق یابد.

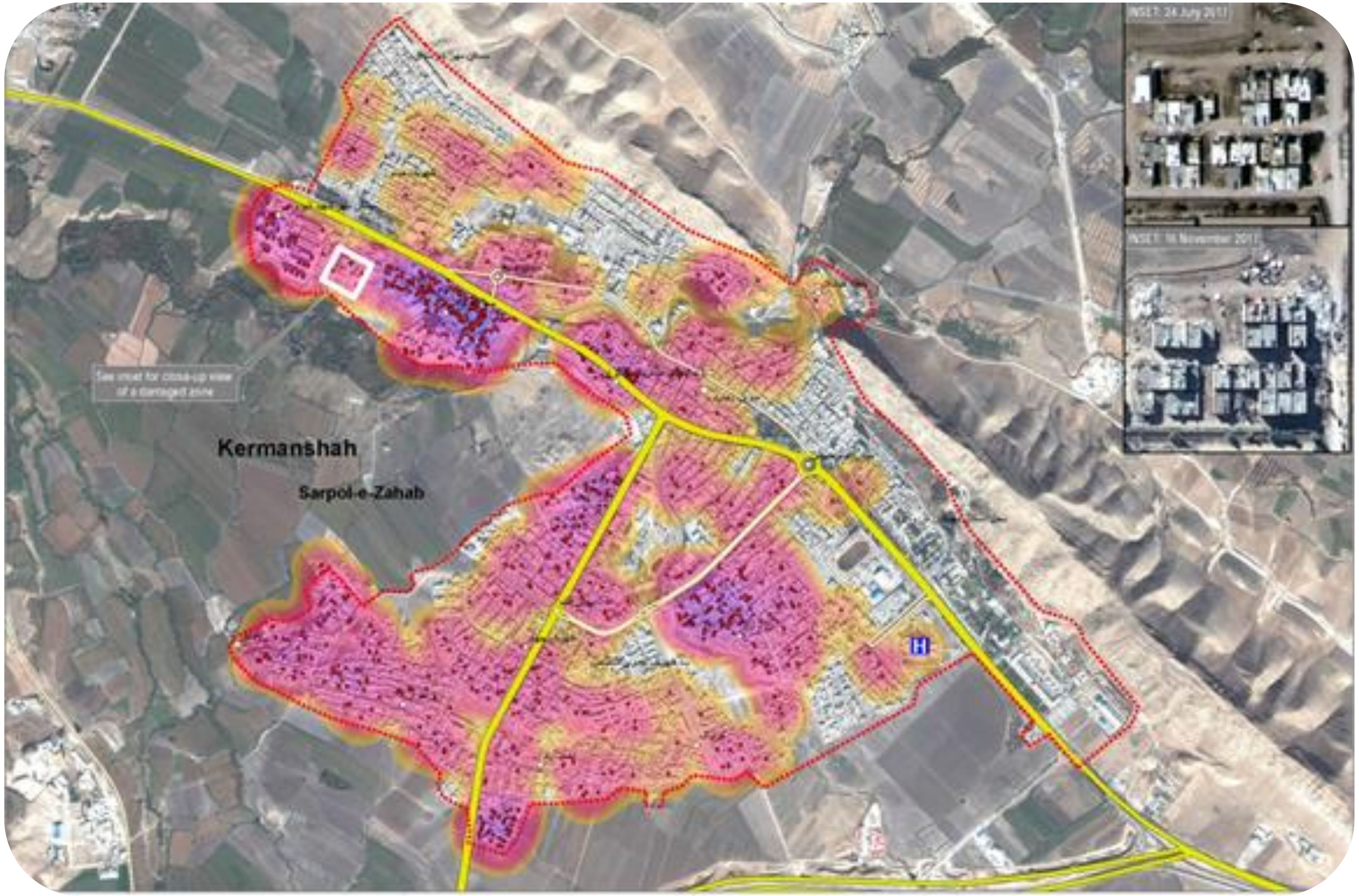


Building Extraction example in Myanmar - Utilizing Deep Learning with Train Data from Iran cases

IRAN Experience

1) Building Extraction
2) Damage Mapping in Disasters

- Satellite Imagery
- VHR Optical Images
- Image Processing
- AI Technology
- Deep Learning



by: UNITAR

Damage Visualized by Optical Imagery – Quickbird Satellite

BAM Earthquake, December 26, 2003

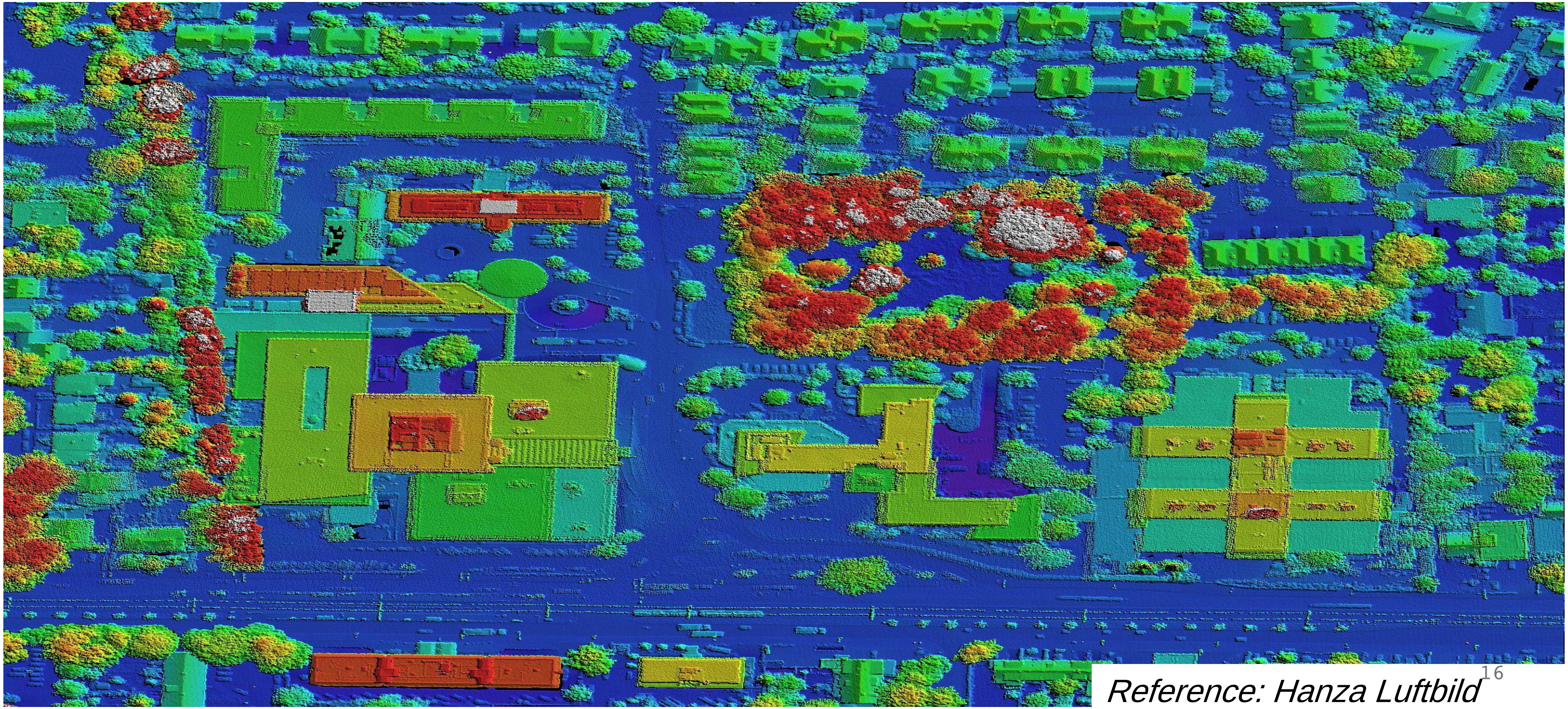
Damage Visualized by Optical Imagery – UAV (Volunteers-Freelancers)

Sarpol-e Zahab Earthquake, December 26, 2003

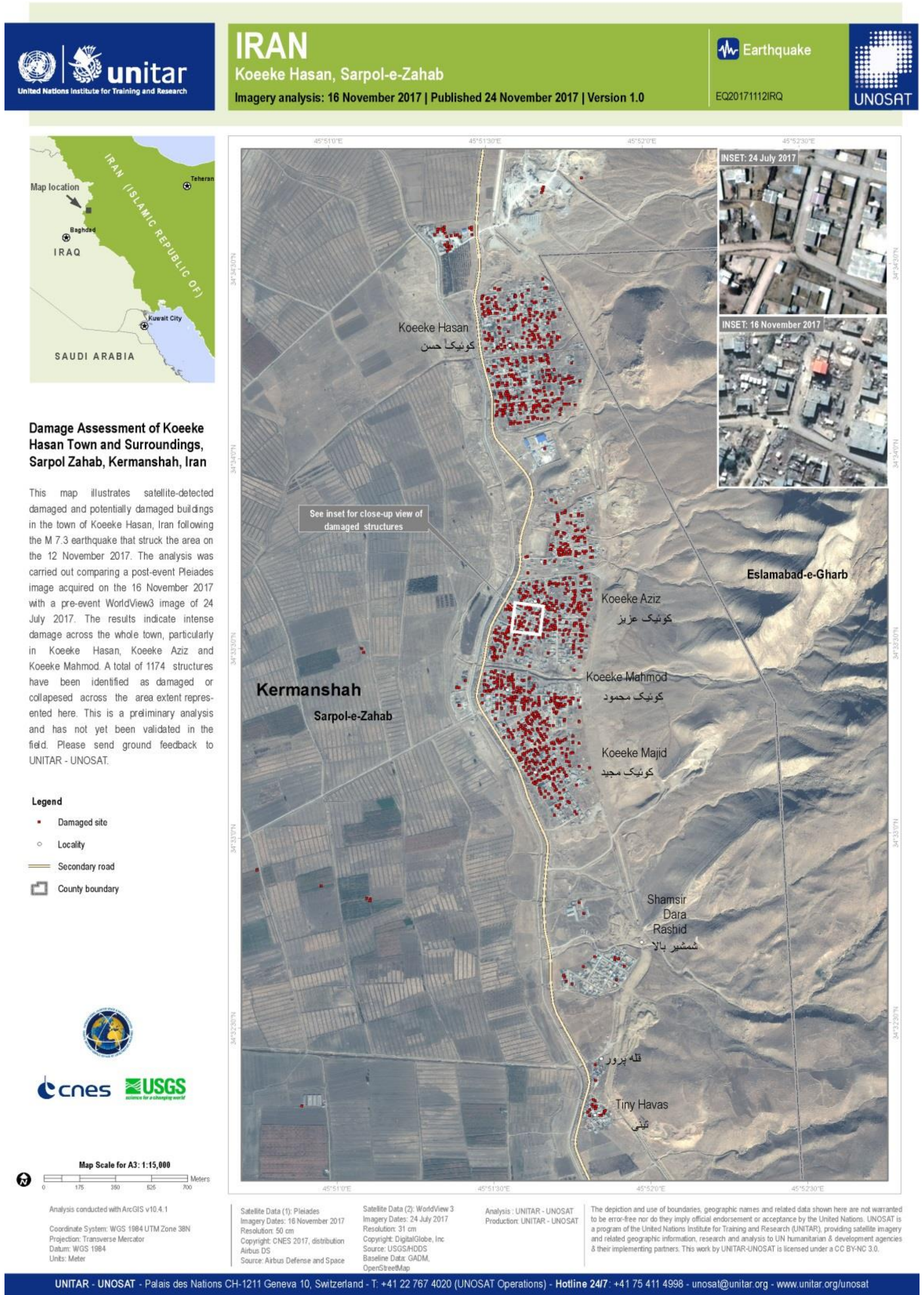
Ezgeleh

LIDAR – Aerial or UAV Systems (Time and Cost concerns)

Excellent results for damage mapping - provides height and albedo information



Reference: Hanza Luftbild



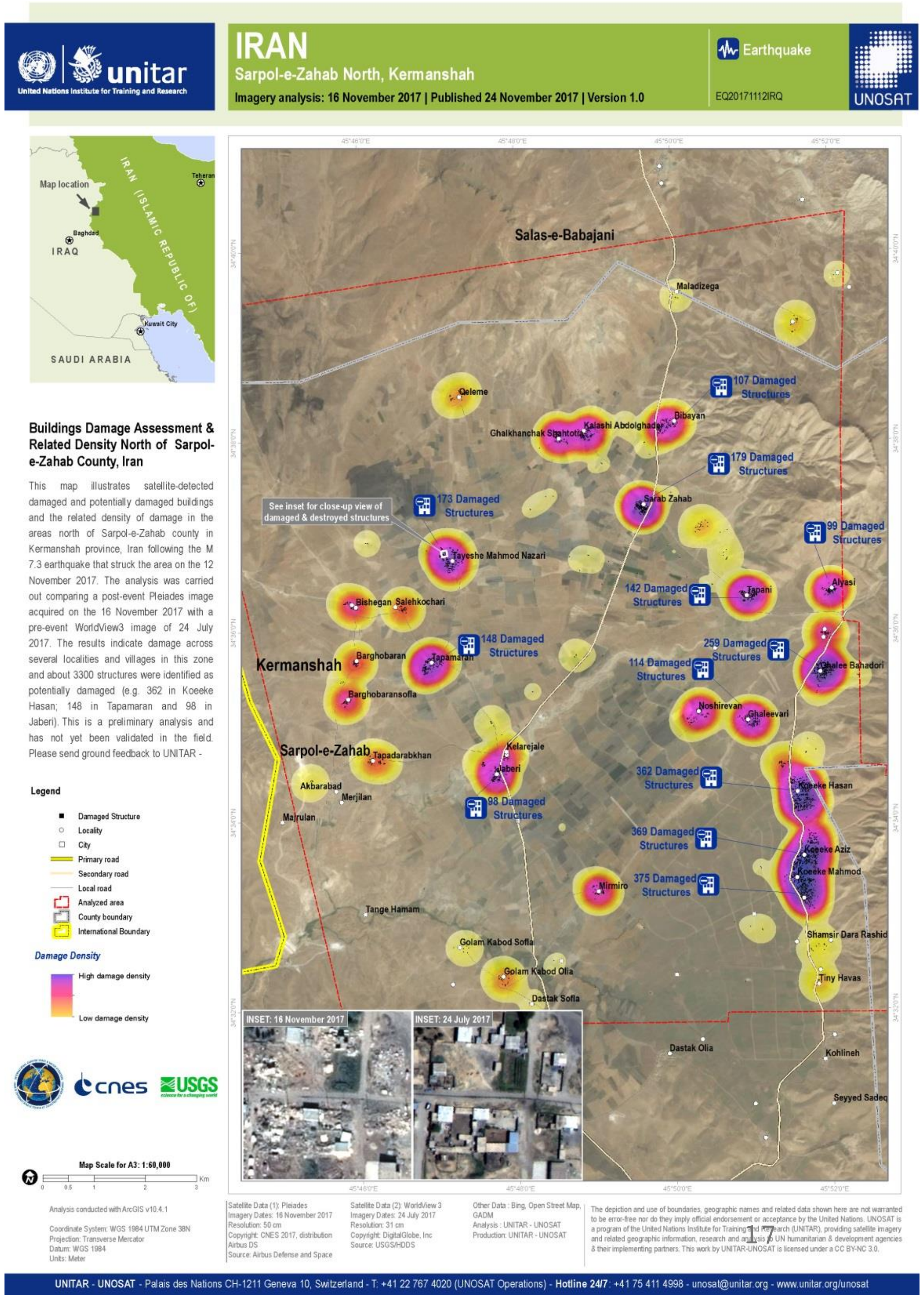
Hard-hit Zones Detected

Manual Damage Mapping

Wolrdwide Operators

OpenStreet Map

Crowd Sourcing

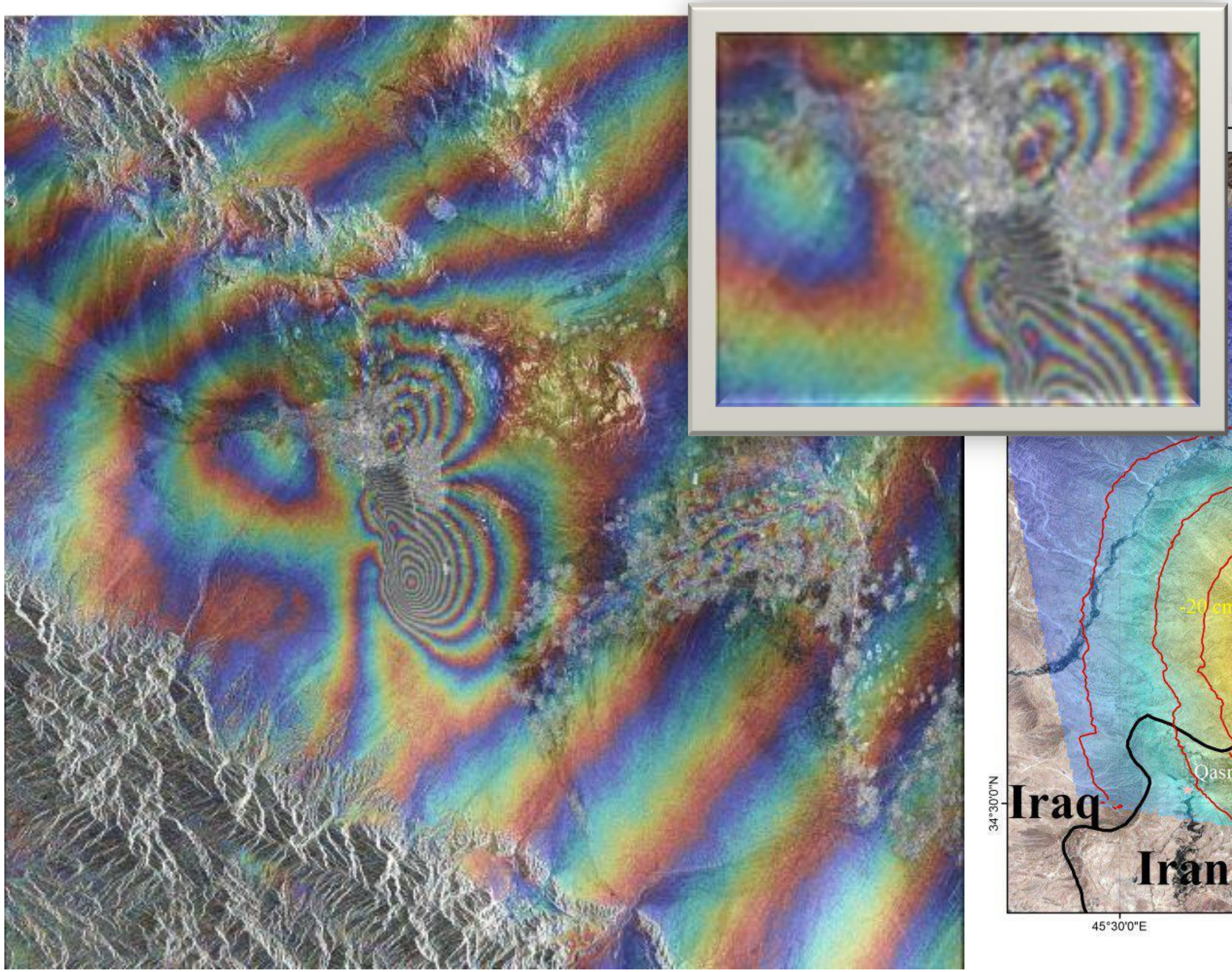


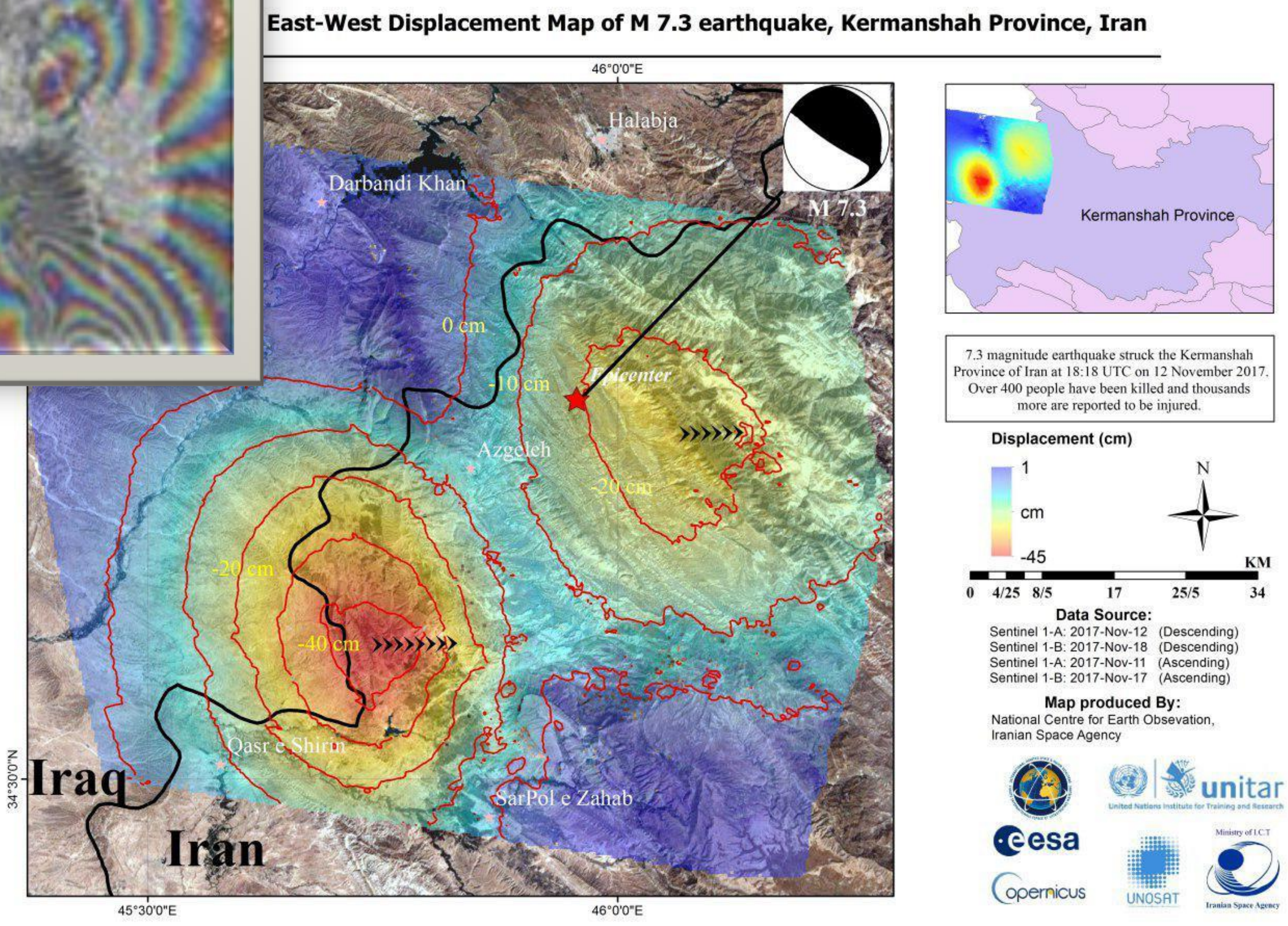
UN-SPIDER

- Space-based information for Disaster Response Efforts
- International Charter "Space and Major Disasters"
- Disseminating satellite based data through "National Space Agencies"

APSCO & Member States Satellites (China, Iran,…)

Crustal Deformation Mapping – Measurement of Coseismic Displacement Field - INSAR Technique





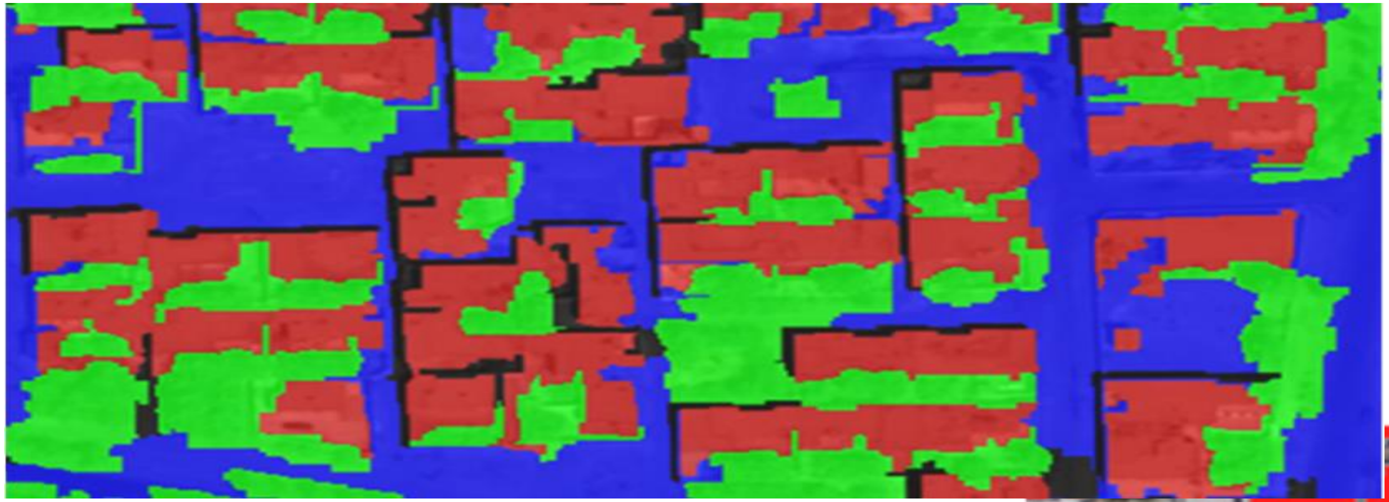
Overview of Previous Work - Spatial Database Development:

Building Extraction

AI Algorithm

(Object-based image analysis – eCognition/Definiens)

Building extraction according to ecognition procedure



Region Merging Technique and Classification

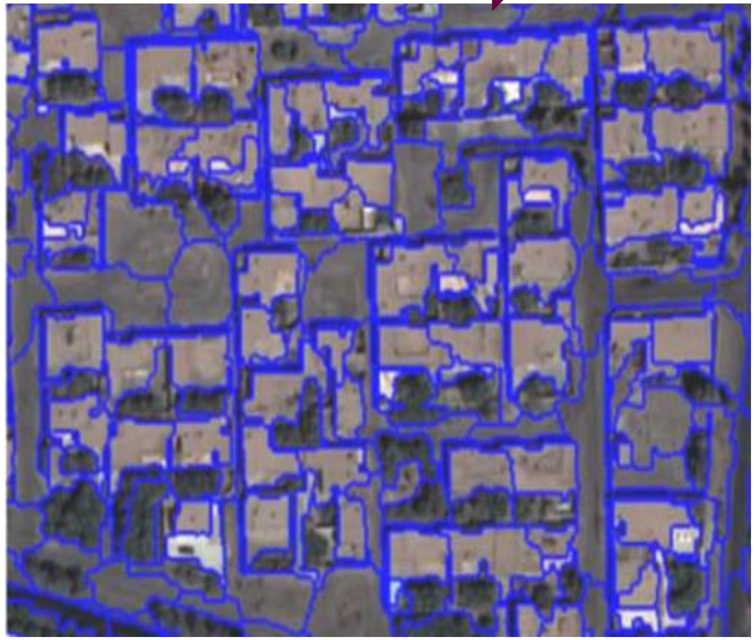
Building Extraction by AI Algorithm (Object-based image analysis by eCognition)

DATASET
(VHR ,UAV)

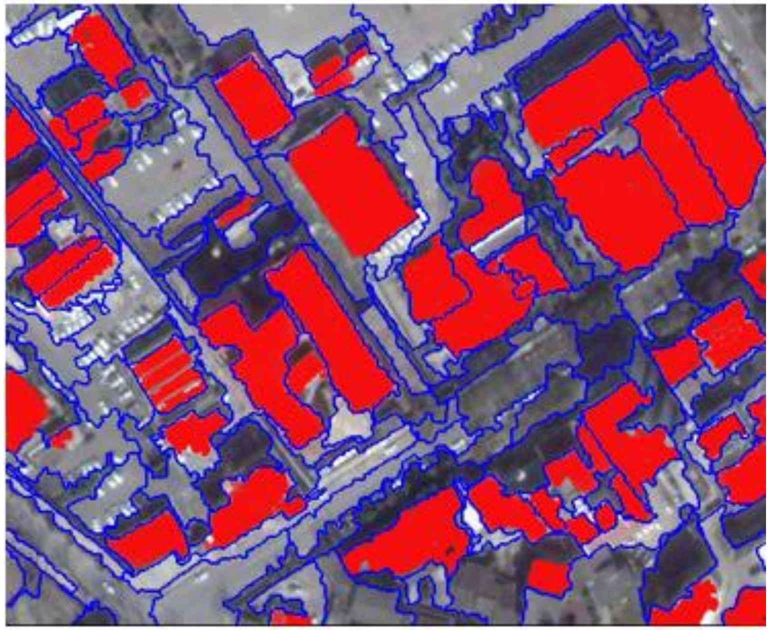
pre-processing
(Geo ref, Co-register, enhancing ,fusion, adjusting, Histogram matching, sharpening ,..)

Classification and segmentation

Building extraction



Segmentation by Region merging Multi-resolution Algorithm



Classification

Building extraction

Overview of Previous Work:

Building Extraction & Damage Mapping

by Artificial Neural Network

(Machine Learning)

Building Extraction and Damage Mapping by Artificial Neural Network (Machine Learning Method)

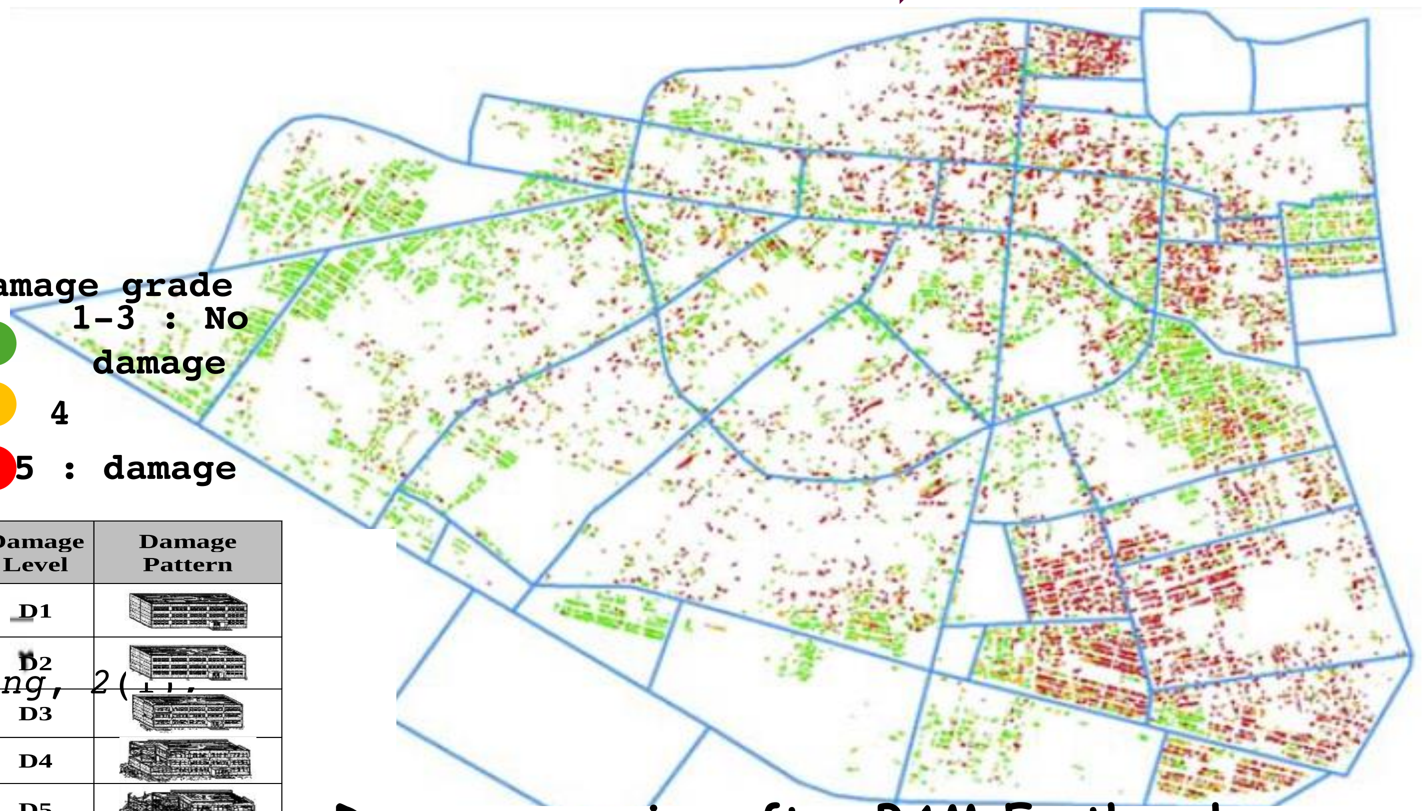
Building extraction → Textural Analysis → Choose optimum Parameters → ANN (Manual Training) → Damage Mapping for BAM

Object-Oriented Building Extraction from VHR Satellite Data and Earthquake Damage detection based on textural Analysis Using Artificial Neural Network

Babak Mansouri
Assistant Professor and Head of Emergency Management Dept. IIEES.
(Corresponding Author). Email: (mansouri@iiees.ac.ir)

Mona Mostafazadeh
Msc Graduate, IIEES

Bulletin of Earthquake Science and Engineering, 2(1), 55-65.



Damage Level	Damage Pattern
D1	
D2	
D3	
D4	
D5	

Damage mapping after BAM Earthquake – by ANN – (2015)

IIEES

Building Extraction and Damage Mapping by Artificial Neural Network (Machine Learning)

IEEE JOURNAL OF SELECTED TOPICS IN APPLIED EARTH OBSERVATIONS AND REMOTE SENSING, VOL. 8, NO. 10, OCTOBER 2015

A Soft Computing Method for Damage Mapping Using VHR Optical Satellite Imagery

Babak Mansouri and Yaser Hamednia

JSTARS - OCT. 2015

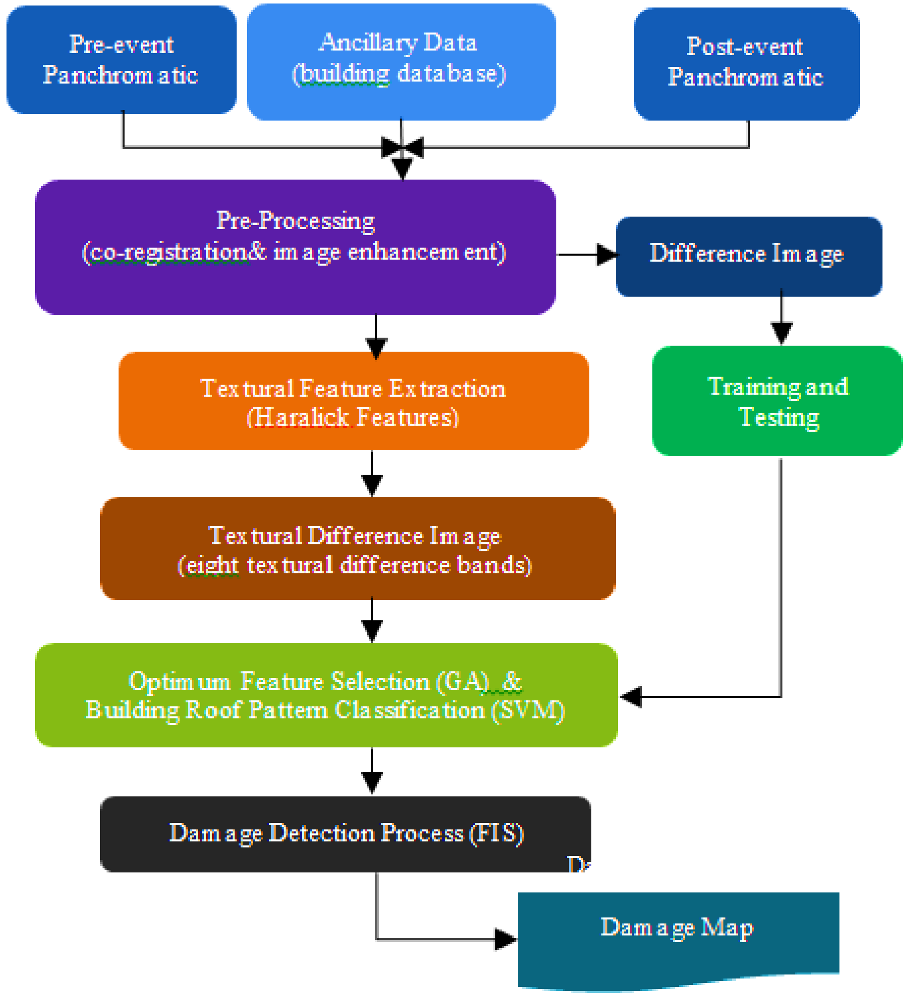
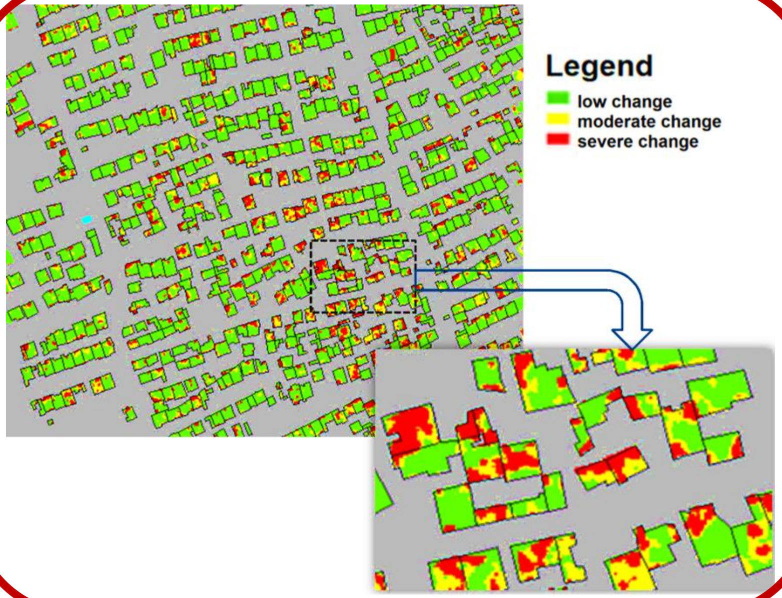
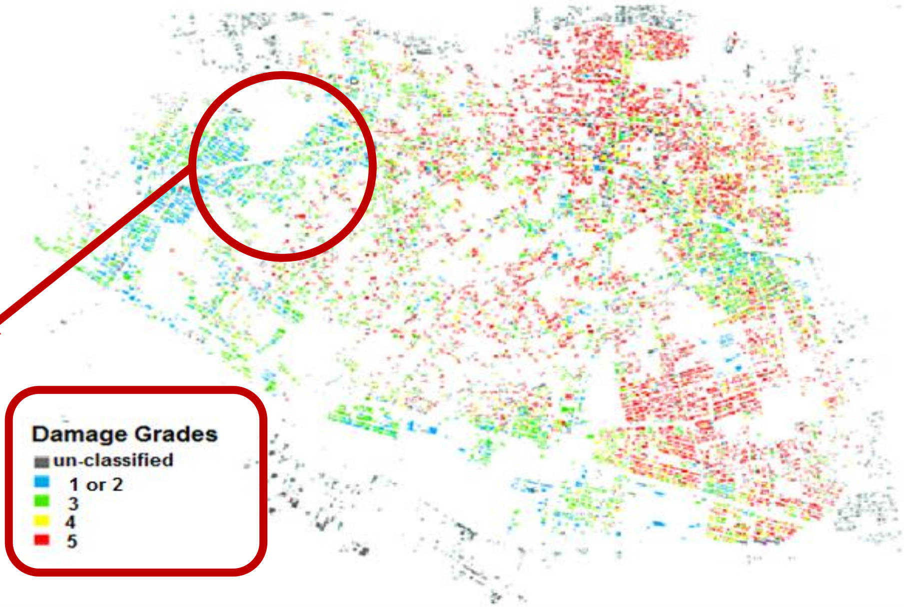


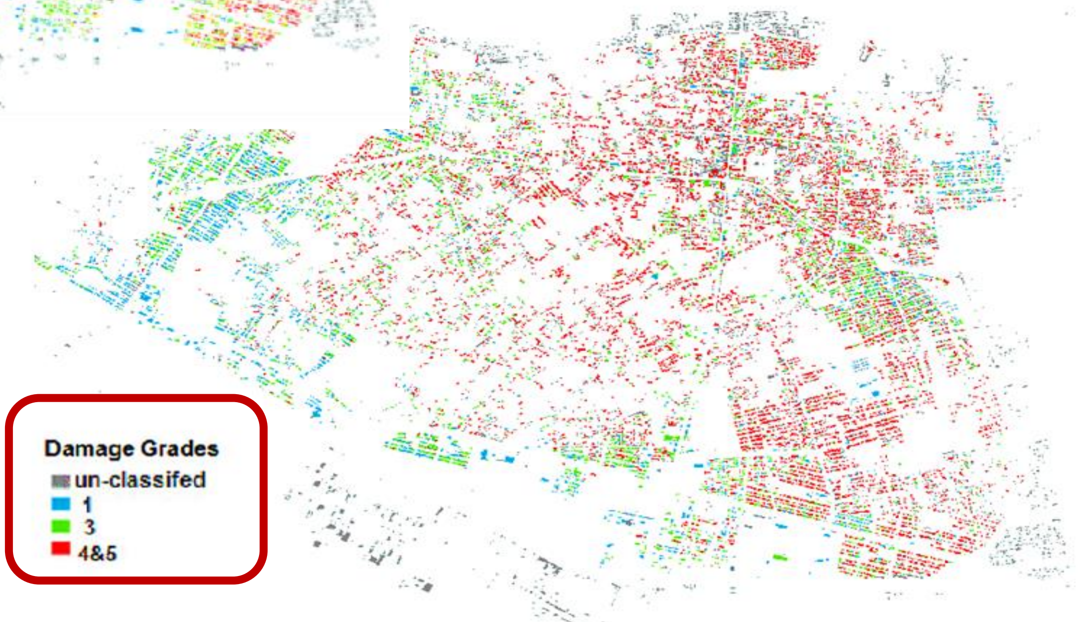
Fig. 1. Flowchart of the proposed method





CONFUSION MATRIX AND RESULTED PA & UA

Confusion Matrix (D1D2,D3,D4D5)		Proposed Method				
		D1D2	D3	D4D5	sum	PA
Reference Data	D1D2	954	508	73	1535	0.62
	D3	893	2135	650	3678	0.58
	D4D5	32	539	5510	6081	0.91
	sum	1657	3214	6423	OA = 0.76 K = 0.59	
	UA	0.58	0.66	0.86		



Damage mapping after BAM Earthquake – by Soft computing method – (2015)

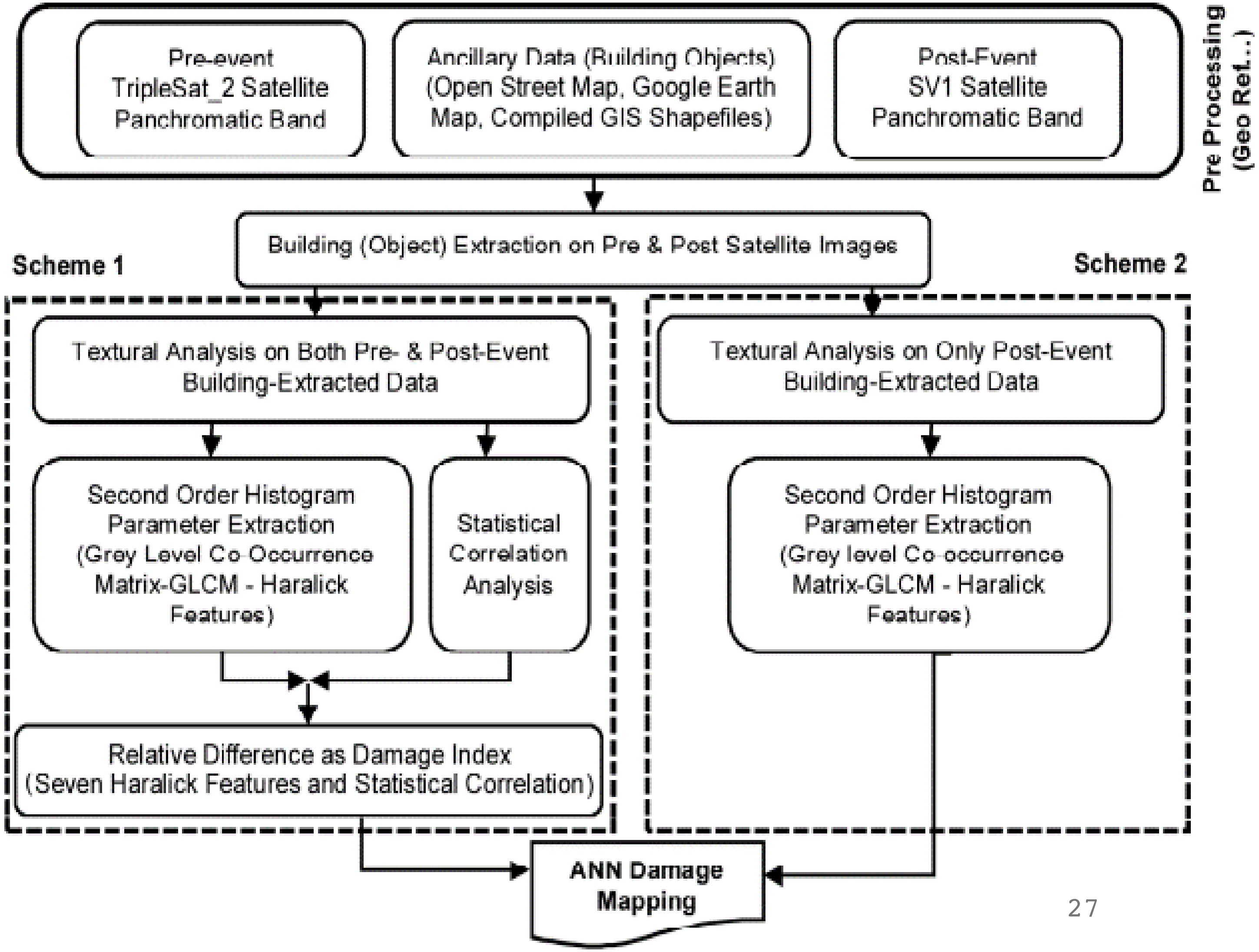
Building Extraction and Damage Mapping by Artificial Neural Network (Machine Learning Method)

Earthquake Building Damage Detection Using VHR Satellite Data (Case Study: Two Villages Near Sarpol-e Zahab)

JSEE, Vol. 20, No. 4, 2019

Babak Mansouri[1], Shakiba Mousavi[2], and Kambod Amini-Hosseini[1]*

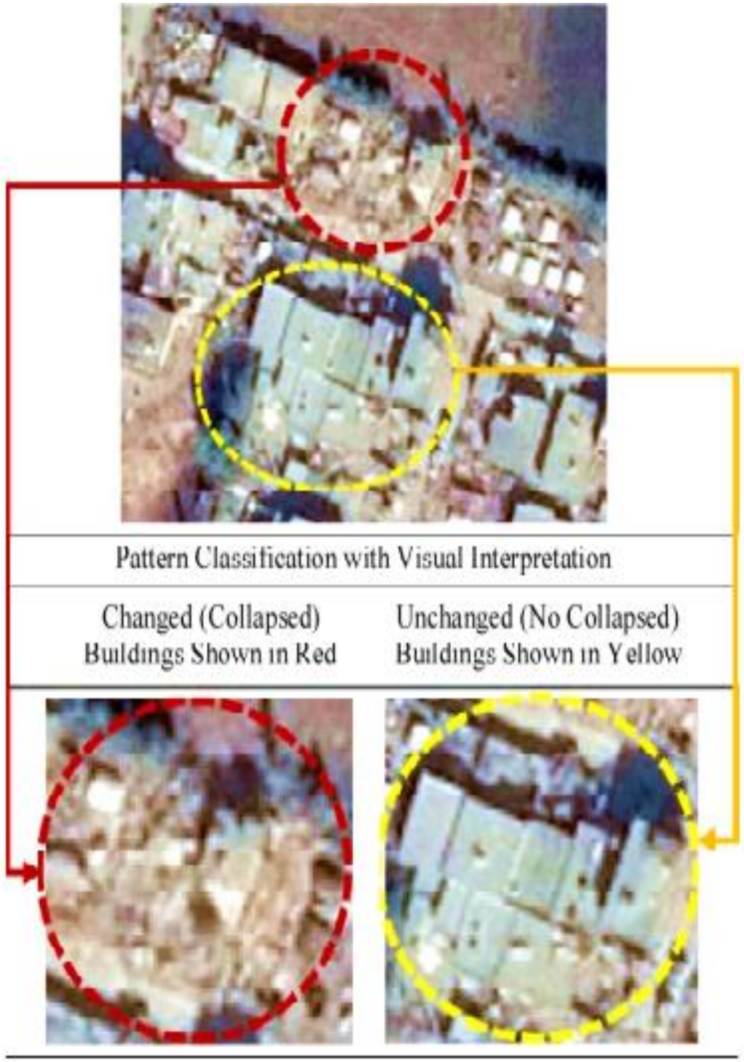
1. Associate Professor, Earthquake Risk Management Research Center, International Institute of Earthquake Engineering and Seismology (IIEES), Tehran, Iran,
* Corresponding Author; email: mansouri@iiees.ac.ir
2. Ph.D. Student, International Institute of Earthquake Engineering and Seismology (IIEES), Tehran, Iran



Satellite data general specification.

Satellite	Spatial Resolution		Acquisition Date
	PAN(m)	MS(m)	
TRIPLESAT_2	0.89	3.2	Pre-event: 2016-06-04
SV1	0.5	2	Post event: 2017-11-16

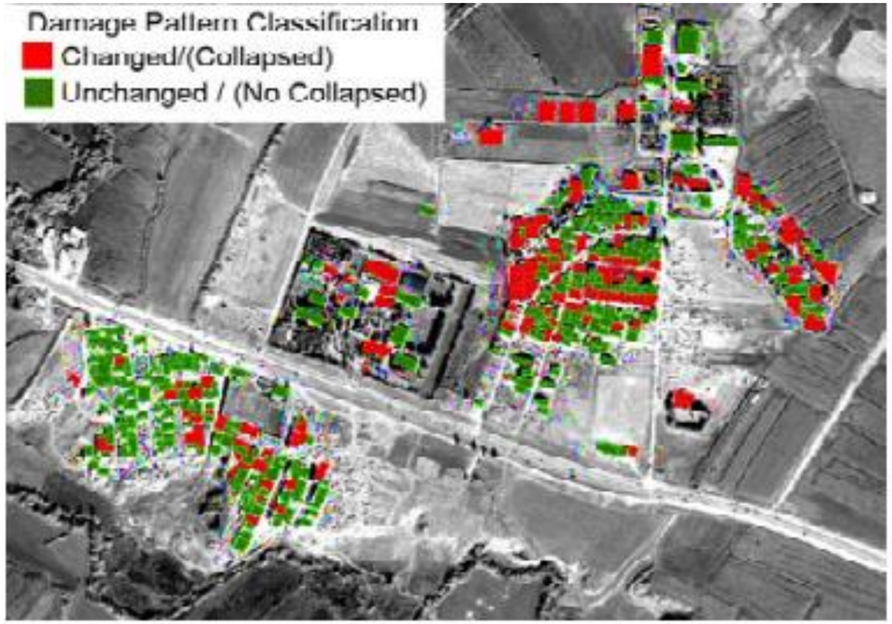
Building Extraction by mask - Manual



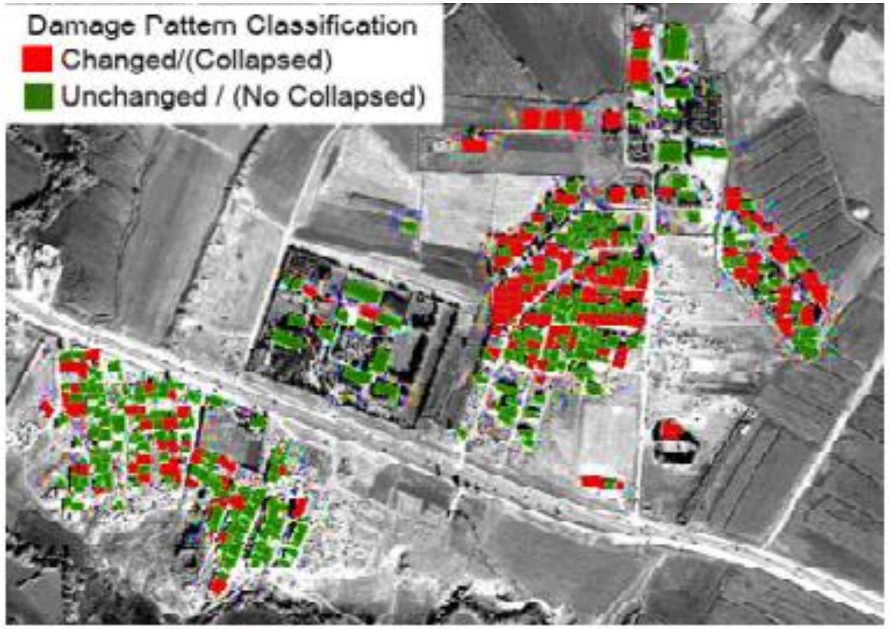
Visual Classification - (Damage - UnDamage)

Satellite	Spatial Resolution		Acquisition Date
	PAN (m)	MS (m)	
Pleiades-1A	0.5	2	16 Nov 2017

Generated Ground Truth Map by visual interpretation of post-earthquake Pleiades-1A satellite image.



Damage mapping for two villages using both pre event and post event images.



Damage mapping for two villages using only post event damage image.

Surprise !!!
OA (B)> OA (A)

(because in A Pre –Imagery quality not as good

ANN's confusion matrix for pre event and post event images.

Confusion Matrix		Reference Data (Ground Truth) Changed/ Collapsed	Unchanged/ No collapsed	sum	UA
ANN Classification	Changed/ Collapsed	76	83	159	0.48
	Unchanged/ No collapsed	50	270	320	0.84
	Sum	126	353	OA = 0.72	
	PA	0.60	0.76		

ANN's confusion matrix for only post event damage map.

Confusion Matrix		Reference Data (Ground Truth) Changed/ Collapsed	Unchanged/ No collapsed	Sum	UA
ANN Classification	Changed/ Collapsed	85	77	162	0.53
	Unchanged/ No collapsed	41	276	317	0.87
	Sum	126	353	OA = 0.75	
	PA	0.68	0.78		

Overview of Recent Work - Spatial Database Development:

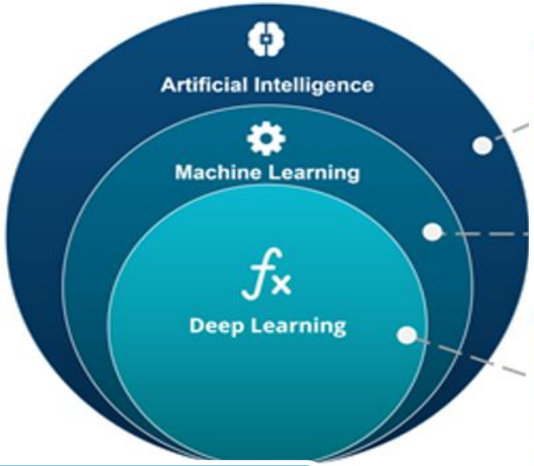
Building Extraction - Damage mapping

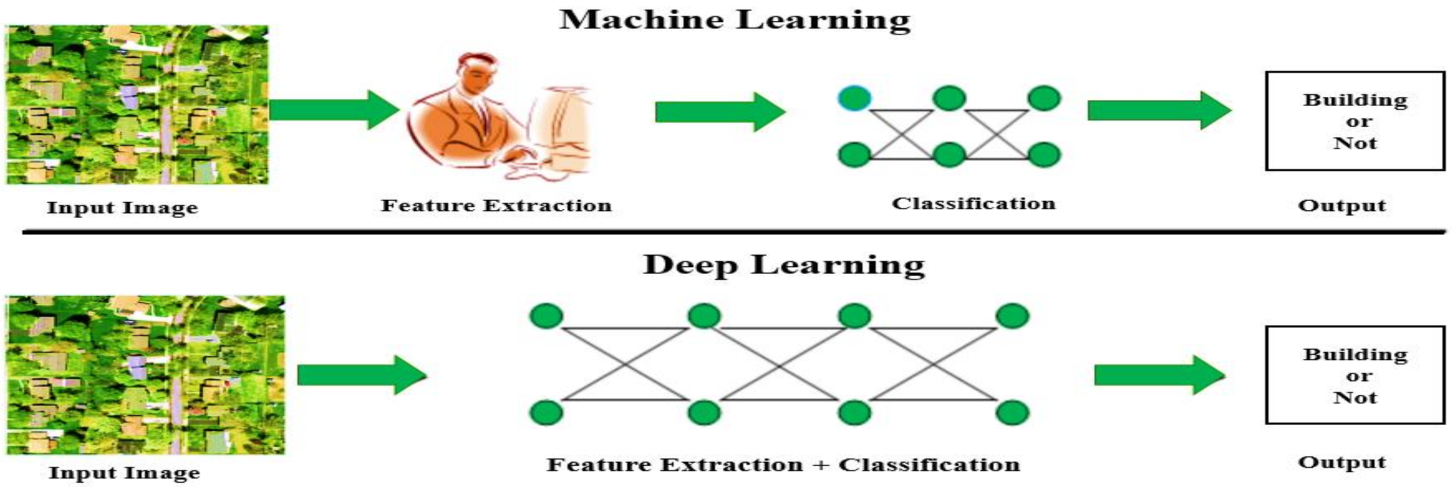
Deep Learning

Babak Mansouri and Shakiba Mousavi

Building Extraction - Damage Mapping

Deep Learning





Dataset preparation

Data preprocessing

- standardize image sizes
- normalize
- Necessary transformations (rotation, scaling, cropping)
- Split the dataset into training and validation sets

DL architecture (Suitable Selection)

- CNN
- U-Net
- FCNs
- R-CNN
- …..

Network training

Iterate over different hyperparameters:

(e.g., learning rate, batch size, regularization techniques) to fine-tune model performance

Evaluation:

Assess trained model performance on separate test dataset

Measure confusion matrix

Overview of Recent Work - Spatial Database Development :

Building Extraction

Deep Learning

Train: Use Available Dataset in the World

Test: UAV images – Sarpol-Zahab- Iran (2017)

World Available Dataset

Space-Net dataset

- 101 labelled sequences
- collected between 2017-2020
- Covering 6 continents 120 km2
- contains over 48,000 building footprint labels.
- consists of multi-sensor data
- (SAR and optical)
- Data for mapping and building footprint extraction.

Massachusetts dataset

- collection of aerial images of the Boston area
- consists of 151 images, Size 1500 x 1500 pixels, covering 2.25 km^2
- spatial resolution 1m

WHU dataset

- manually labeled dataset
- created by researchers at Wuhan University in China
- dataset includes HR aerial images of various urban areas in China covering 12 different cities
- captured between 2006 -2012

Massachusetts RS dataset

- covers a 500 km2 surface area
- Include suburban areas to rural areas
- included ground object (roads, oceans, buildings, tree, bridges, and vehicles)
- RS image is comprised (RGB) bands
- image size 1,500 × 1,500 pixels
- spatial sampling resolution of each pixel is 1.2 m

WHU-Mix Dataset

- diverse, large-scale, high-quality
- recently introduced
- training/validation set 43,727 images from all over the world
- test set containing images from 5 other cities on five continents

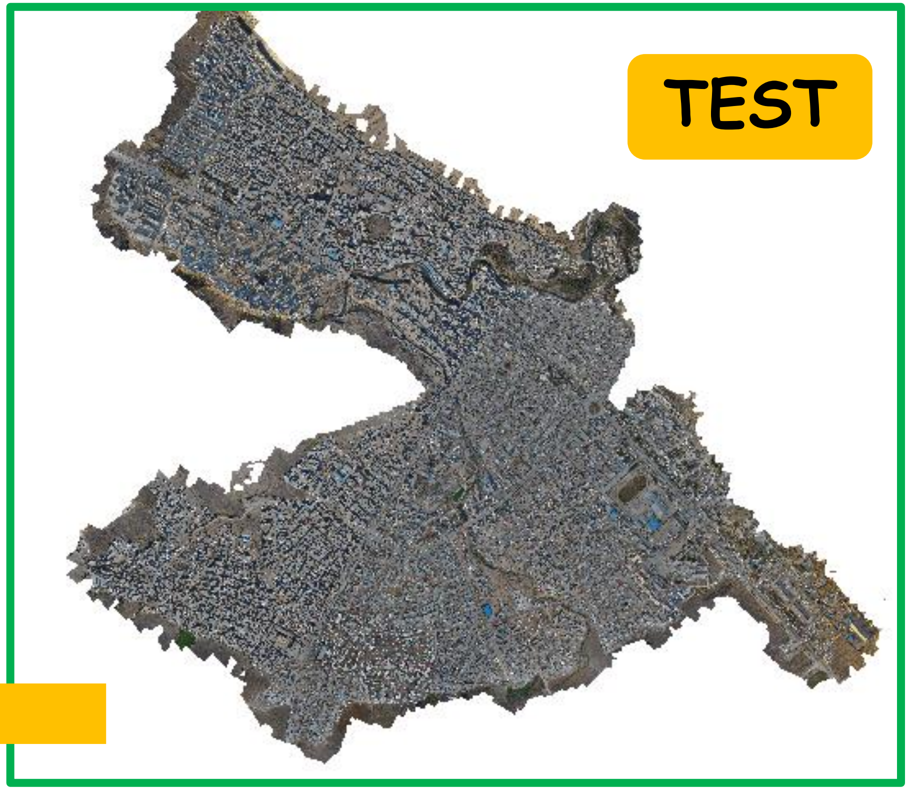
Original Massachusetts dataset

- contains 1,171 images
- expanded dataset (two-stage data expansion method)
- Expanded-dataset 5,540 RS images
- 3,878 images the train dataset
- 1,108 images the validation dataset
- 554 images the test dataset.

TRAIN

TEST

DATASET	Location	Sensor	Resolution (m)
Indianna (Train)	Urban / Sub-urban	Ariel imagery	0.3
WHU-I (Train)	Urban	Satellite	0.3 – 2.5
Sarpol-Zahab (Test)	Urban / Sub-urban	UAV	0.15



Auto-Encoder Architecture

convolutional neural network for semantic segmentation and classification

conv2Dblock + ReLU+ Batch normalization

MaxPooling

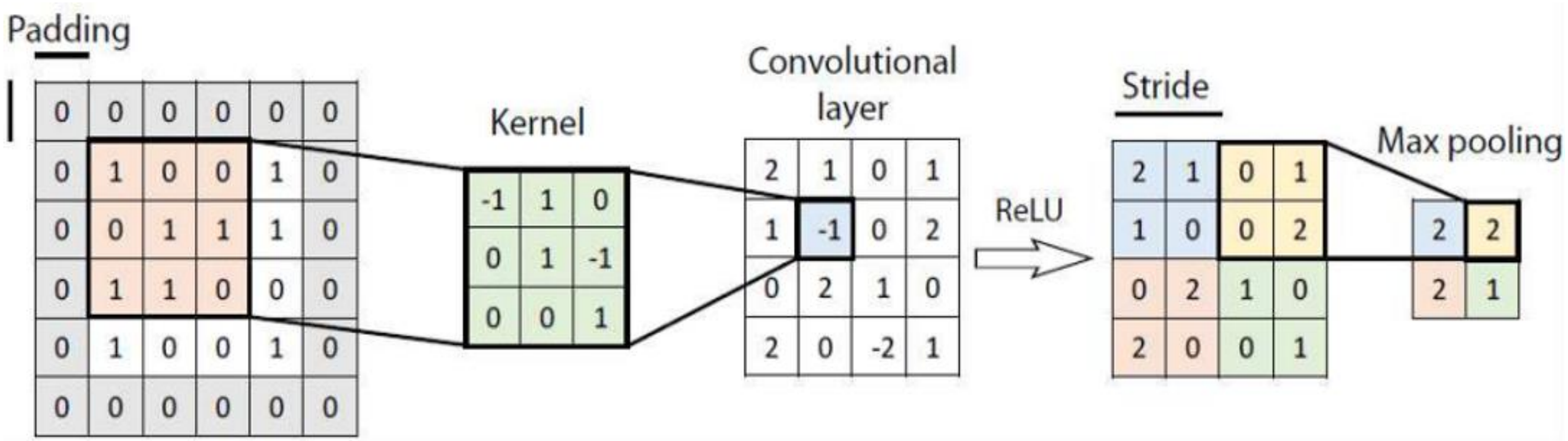
Up Sampling

Dropout

Conv2d

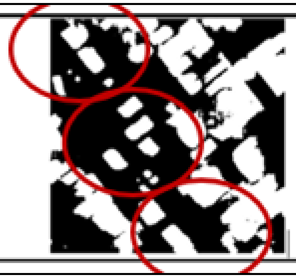
Soft max

Cross-entropy



Results & Conclusion

No.	Test images	Ground truth	Predict
1			
2			
3			
4			
OVERAL ACCURACY %			82%

Test images	Ground truth	Predict
		

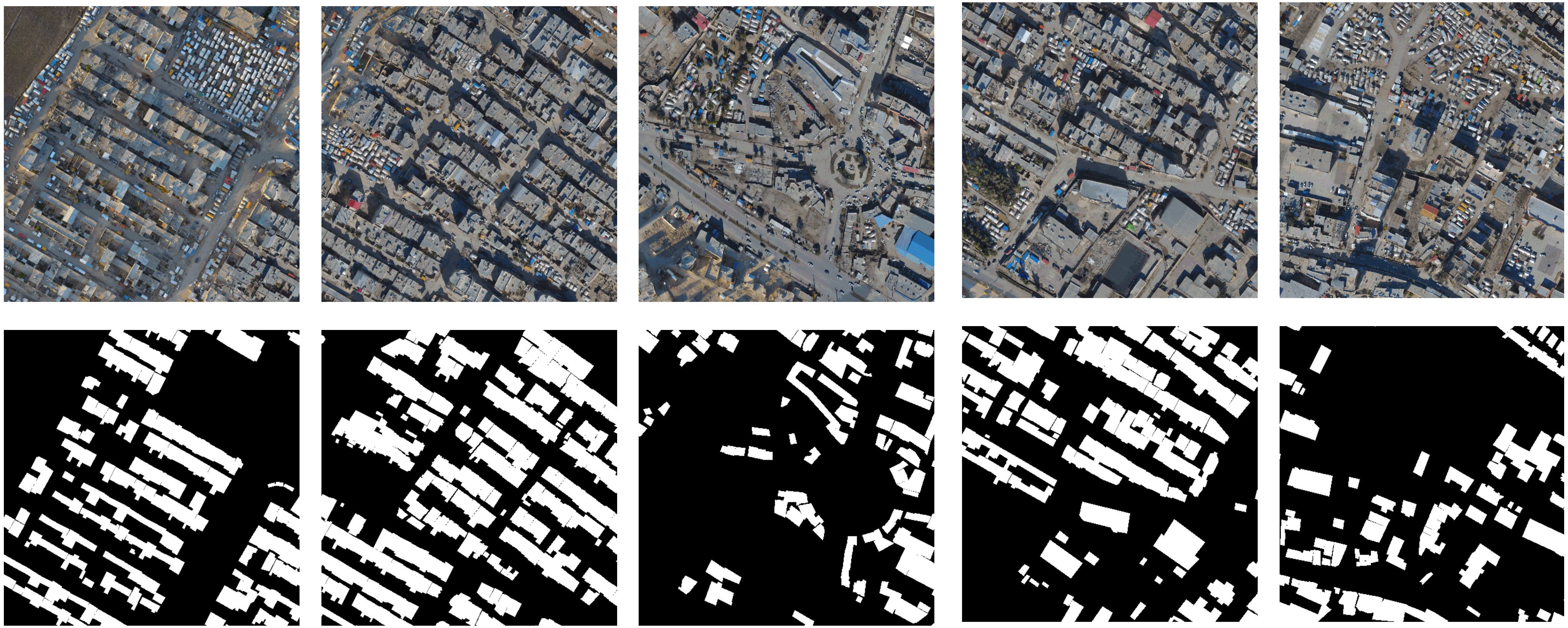
Overview of Recent Work - Spatial Database Development:

Building Extraction

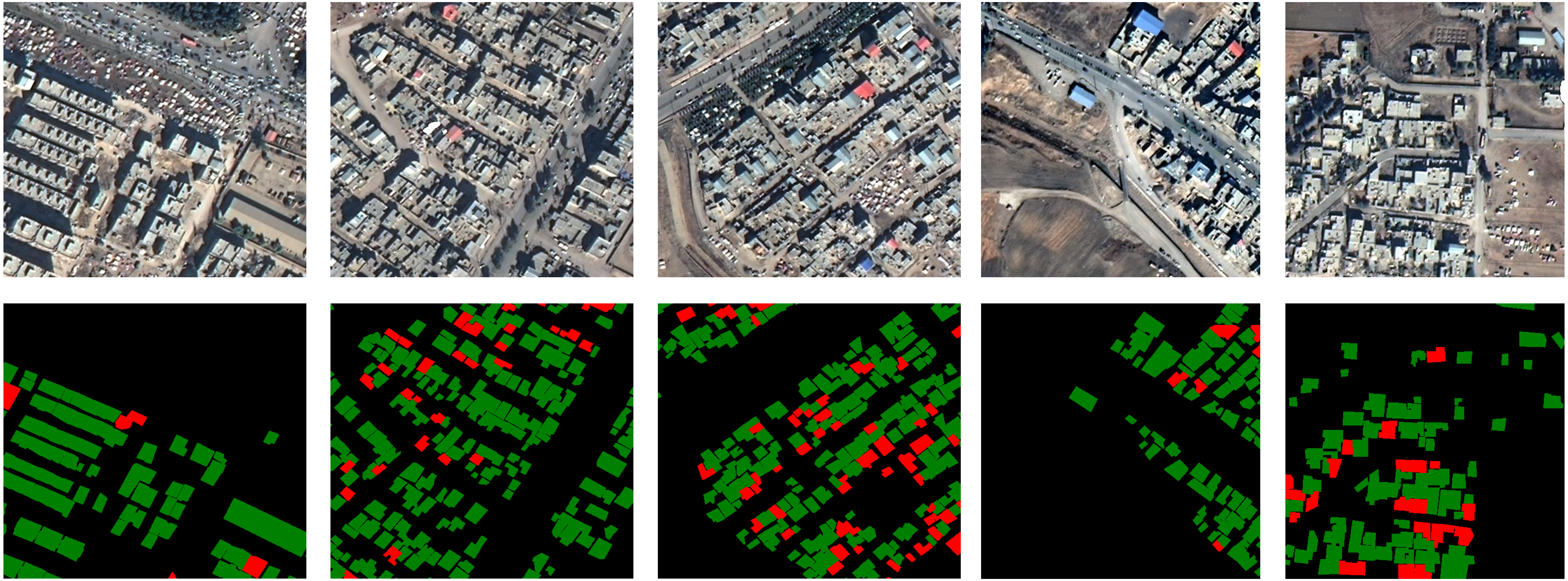
Deep Learning

Train & Test:
Domestic Dataset (Home Made)
Satellite & UAV Imagery
Sarpol-Zahab- Iran (2017)

Domestic dataset created – Building Extraction



Domestic dataset created – Damage Mapping



IIEES

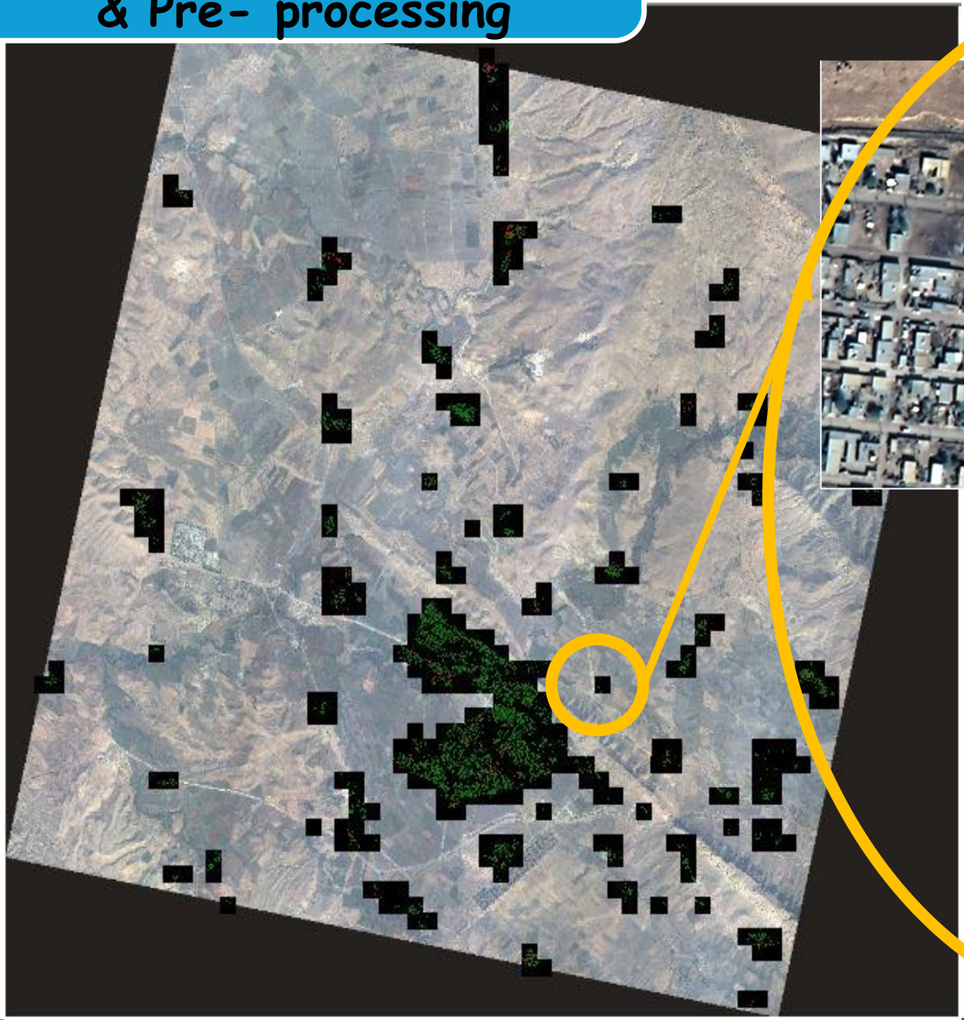
Generate Our Dataset data preparation & Pre- processing

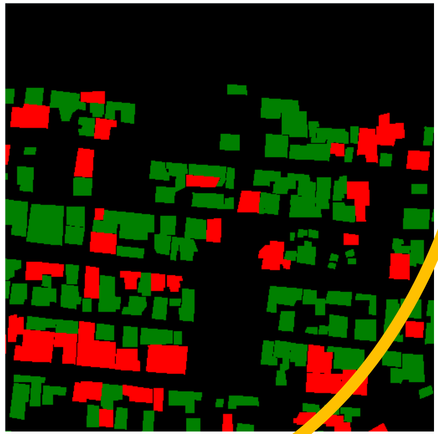
TRAIN Dataset :

- RGB (N images - 512*512 and larger)
- Ground Truth (N images- 512*512)

TEST Dataset :

- RGB (N images - 512*512 and larger)
- Ground Truth (N images- 512*512)



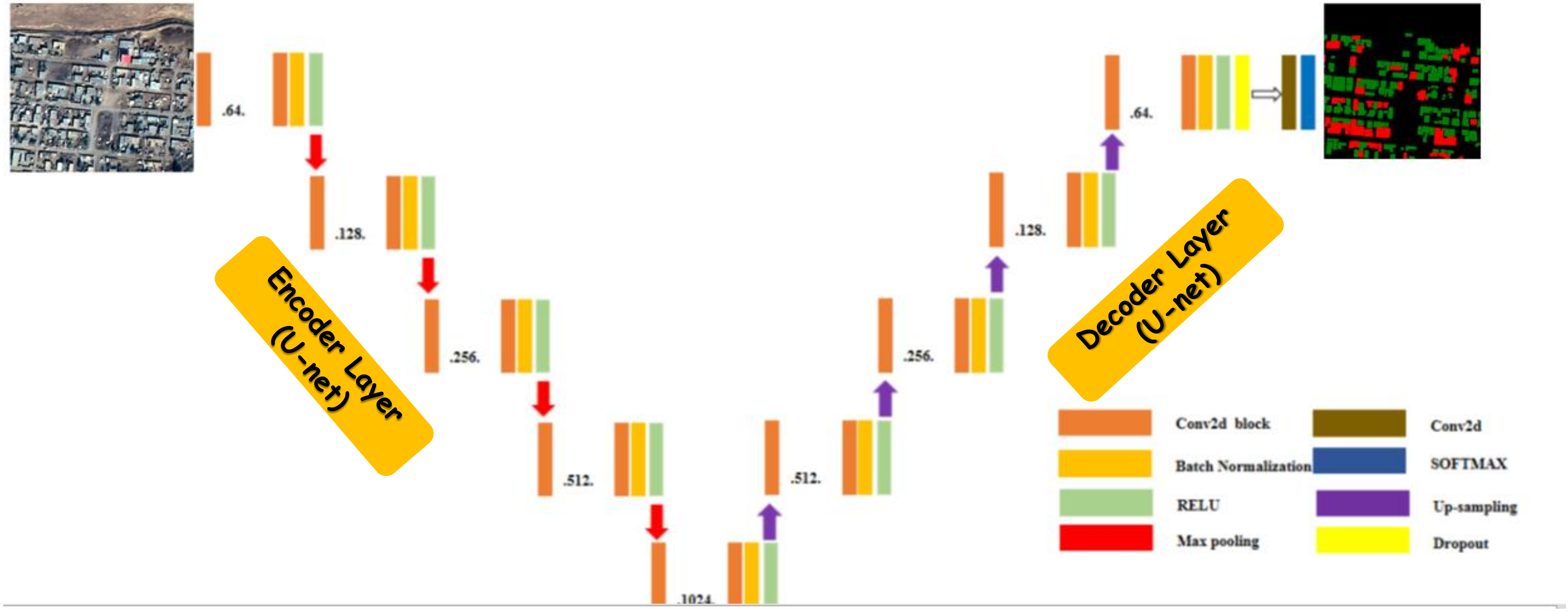


Captured by Super View -1 Satellite

Sarpol - Zahab Provience that Captured by Super View -1 After 2017 Earthquke	
Width	33936 pixel
Height	33084 pixel
Band	3 Band (RGB)
Pixel Size	0.5-0.5 (m)

No. of Masks (manual)	17790
No. Damage buildings	15949 (90%)
No. un-Damage buildings	1841 (10%)

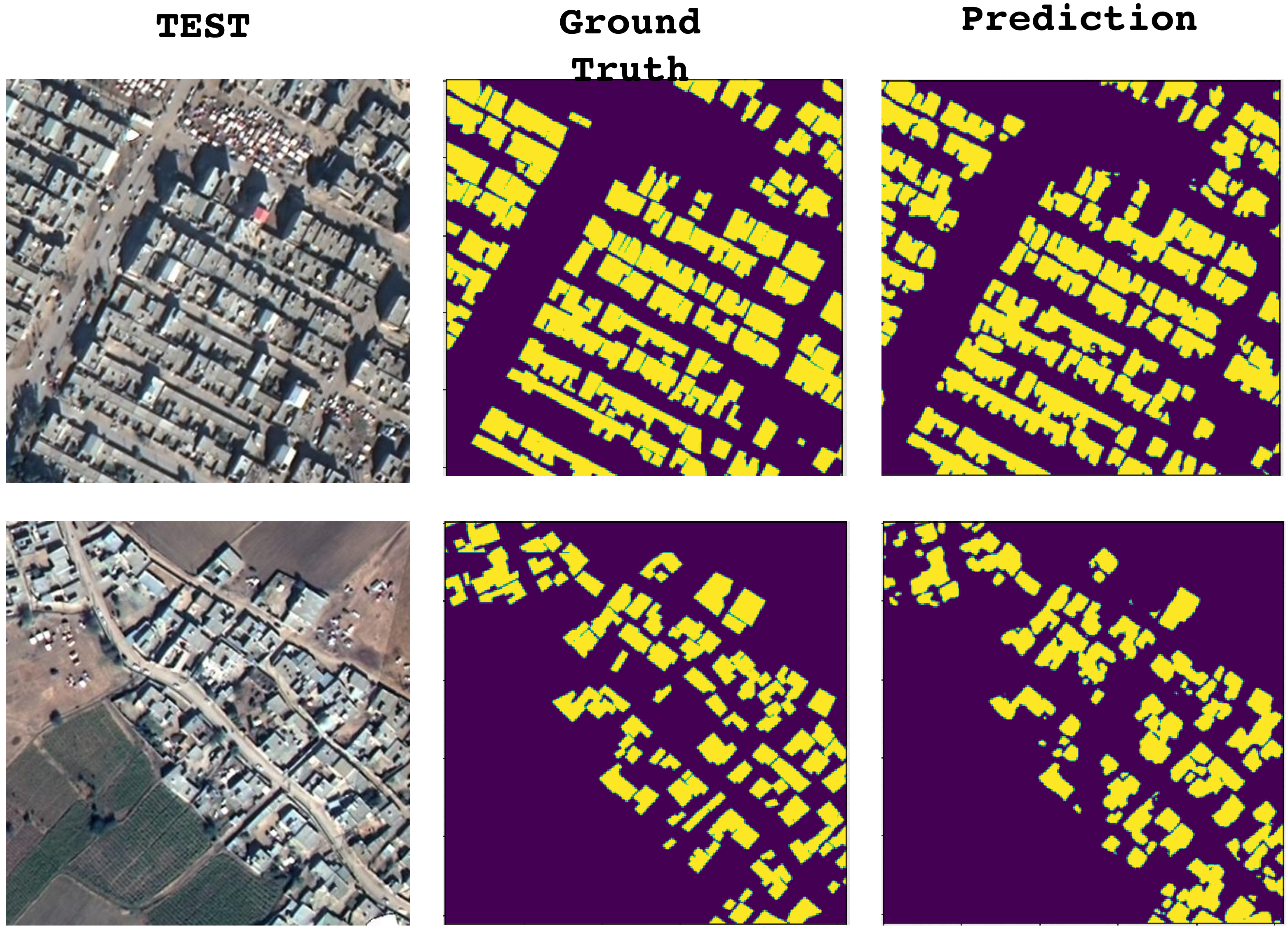
Example:
Proposed U-net network



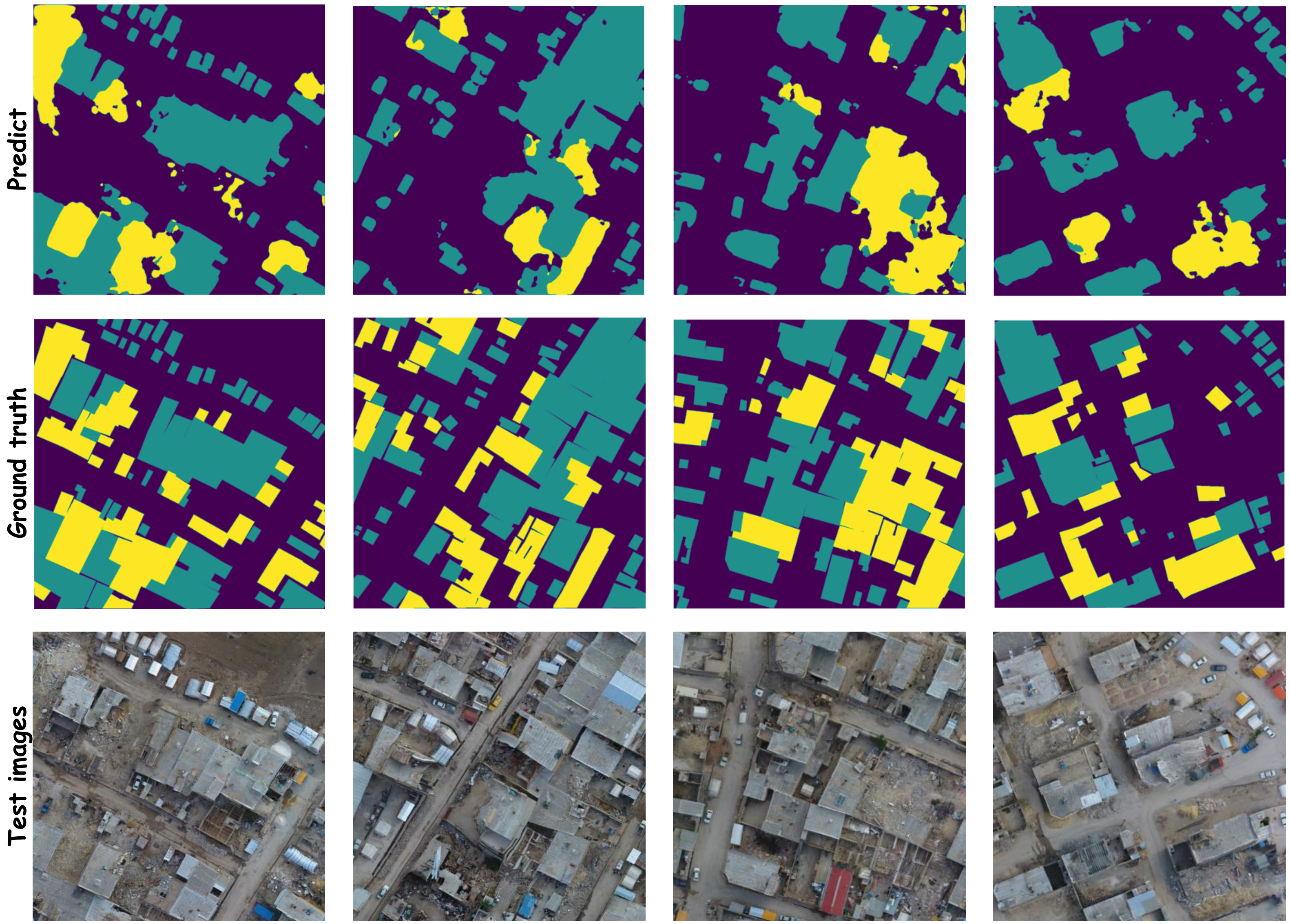
Building Extraction for Auto-Encoder Architecture

OA:92%

Kappa:74%



Damage Mapping



Class	Accuracy	Kappa
Damage	88%	72%
Undamage	93%	82%

انتقال یادگیری: (Transfer Learning)
چالش اصلی در فرآیند آموزش مدل‌های یادگیری عمیق در استخراج نقشه خرابی: **کمبود داده‌های برچسب‌خورده** (labelled data) برای زلزله جدید

مفهوم:
استفاده از دانش مدل‌های آموزش‌دیده روی مجموعه‌داده‌های بزرگ و مشابه برای حل مسائل جدید با داده‌های محدود است.

به جای آموزش یک مدل از صفر (که زمان‌بر و داده‌بر است)، یک مدل پیش‌آموزش‌دیده (Pre-trained) بر روی داده‌های خاص مسأله جدید تنظیم یا (Fine- Tune)می گردد.

کاربرد در پروژه زلزله میانمار:
مدل‌های **پیش‌آموزش‌دیده روی مجموعه‌داده‌های عمومی** مانند ImageNet یا داده‌های سنجش از دور مشابه، انتخاب می گردد.
این مدل‌ها در درک ویژگی‌های تصویری مانند لبه‌ها، بافت‌ها و الگوهای خرابی، **دانش اولیه** را دارند.
مدل با تعداد کمی تصویر برچسب‌خورده از زلزله مورد نظر **تنظیم مجدد** می گردد تا با ویژگی‌های خاص منطقه تطبیق یابد.

مزایای انتقال یادگیری:
کاهش نیاز به داده‌های زیاد: کافی است تعداد کمی تصویر برچسب‌خورده تهیه شود.
صرفه‌جویی در زمان و منابع محاسباتی: آموزش مدل جدید از صفر زمان‌بر است، ولی فاین‌تیون بسیار سریع‌تر انجام می‌شود.
افزایش دقت: مدل می‌تواند ویژگی‌های پیچیده خرابی را بهتر یاد بگیرد.

تشکر از توجه شما